Validating the Performance of Forecast Models in the Case of Limited Historical Data

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Performance of Forecast Model:

- The performance of a forecast model is determined based on:
  1. Forecast Accuracy.
  2. Computational Efficiency (i.e. computational time or hardware resources).

- In terms of importance (generally):

Forecast Accuracy $\geq$ Computational efficiency

Performance Validation:

1. Apparent Validation: model performance is tested based on the training dataset.
2. Internal Validation: split the data into two categories: one for training and one testing (i.e. Cross Validation or Bootstrap).
3. External Validation: test the model on newly available data (not used in training).

Trade-off Advantages and Limitations:

Validation	Advantages	Limitations
Apparent	Always applicable	NOT a sufficient measure (i.e. overfitting)
Internal	Good performance measure	NOT efficient in case of small dataset.
External	Good performance measure	NOT an always available option.

Validation in case of Limited Historical Data

Is there a way to validate a forecast model in case of small datasets?.

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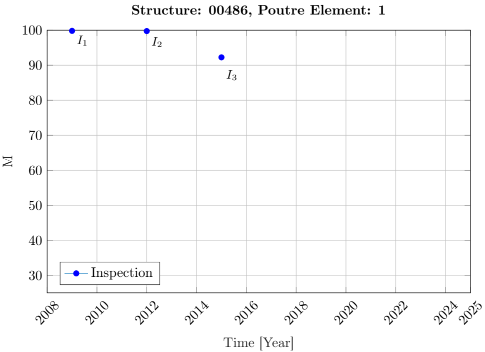
An example (Visual Inspection Data):



Limited Data Validation Methods:

Two methods can be used in the case of limited data:

1. Validation through Simulation.

2. Panel Data Cross Validation.

Validation through Simulation

- The model is tested on synthetic data that consumes the same characteristics of the original data.

- Advantages:
  1. Create a sufficient data to test the model through different validation methods.
  2. Validation vs. the true state is possible. (i.e. excluding the measurement error)
- Limitation:
  1. The synthetic data represents only what we put in it.

Quick Recap

MDMDET Visual Inspections database of bridges.

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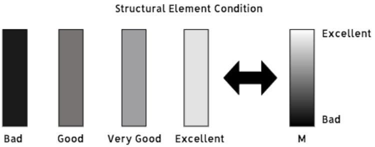

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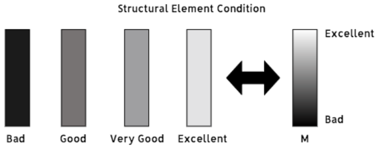
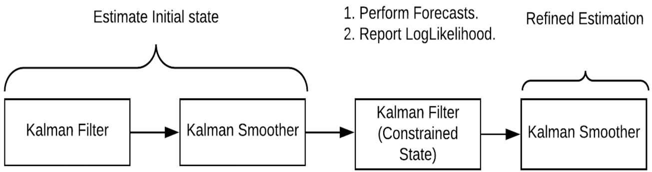


The employed forecast model is Kalman Filter:



Main KF Framework Parameters

1. Model Uncertainty (σ_w).
2. Observation Uncertainty (σ_{V_i}) that includes:
   2.1. Inspector Based Uncertainty (Subjective Observations).
   2.2. Condition Based Uncertainty.

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Additional KF Framework Parameters

1. Initial Guess $(M_{t=0}, \dot{M}_{t=0}, \ddot{M}_{t=0})$ (Tuned by the smoother).
2. Initial Guess $(\sigma_{M_{t=0}}, \sigma_{\dot{M}_{t=0}}, \sigma_{\ddot{M}_{t=0}})$ (Tuned by the smoother).

Why?

Additional KF Framework Parameters

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2. Initial Guess ($\sigma_{M_{t=0}}, \sigma_{\dot{M}_{t=0}}, \sigma_{\ddot{M}_{t=0}}$) (Tuned by the smoother).

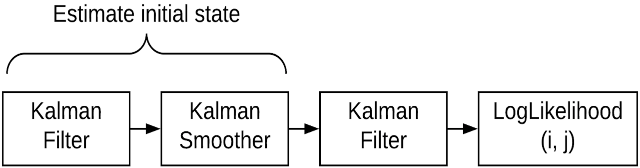
Why?
The time series (where we have data) is too short that it can be too sensitive to the initial guess.

Objective

- Define different frameworks to estimate all the aforementioned KF parameters.
- Select the best framework through a validation process.

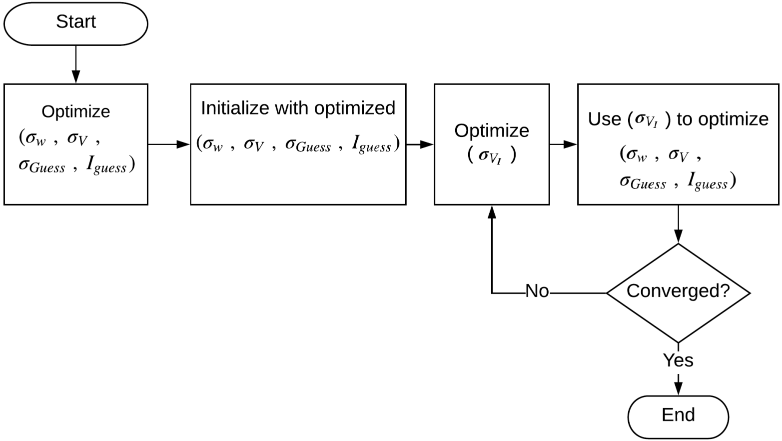
KF Parameter Estimation Frameworks Assumptions

- All frameworks share the same objective: $Max. \sum Loglikelihood(i, j)$ for all structural elements.
- The $Loglikelihood(i, j)$ for structural element(i) and observation (j) is computed as follows:



- In all frameworks, the parameters are optimized using the same optimization algorithm: *NewtonRaphson*.

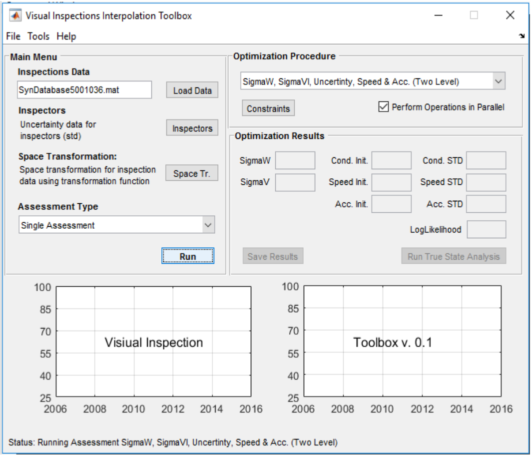
Main KF Parameter Estimation Framework



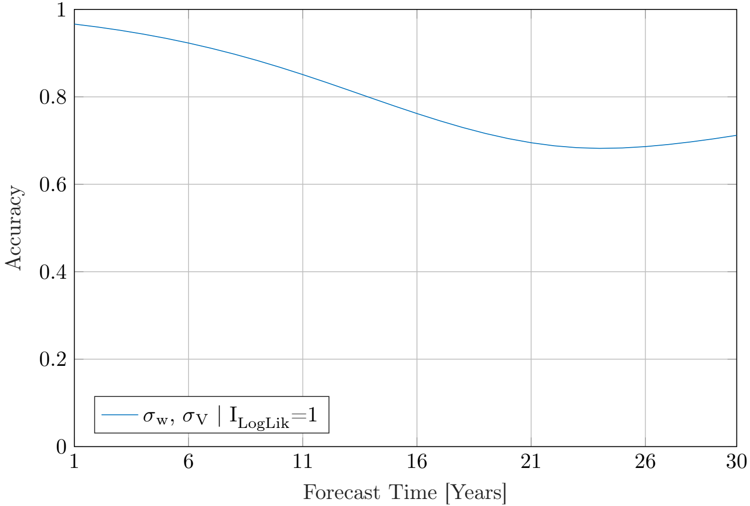
Generating Synthetic Data

1. Generate Inspectors IDs.
2. Generate Inspectors standard deviation within a known range.
3. Allow an inspector to inspect a structural element multiple times through grouping and shuffling.
4. Generating the synthetic state and observations:
   $x(t+1) = A * x(t) + w \ \ : w \sim \mathcal{N}(zeros, Q)$
   $y(t+1) = F * x(t+1) + v \ \ : v \sim \mathcal{N}(0, \sigma_{v_i})$
5. Constraints:
   Hard constraint: speed & acc ≤ 0
   Soft constraint: $y(t+1) \leq y(t)$

Visual Inspections Toolbox



Average Accuracy Performance



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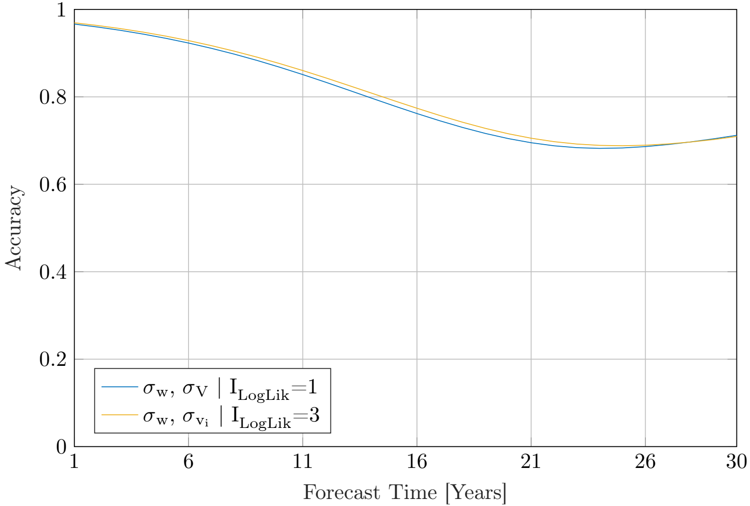

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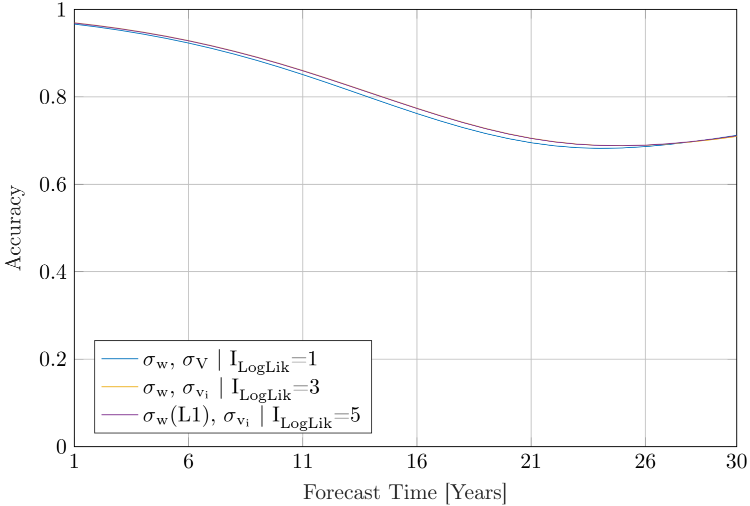

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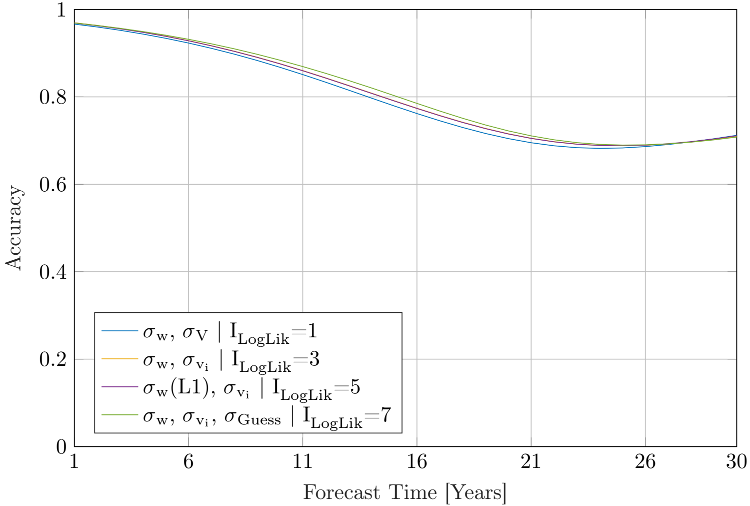

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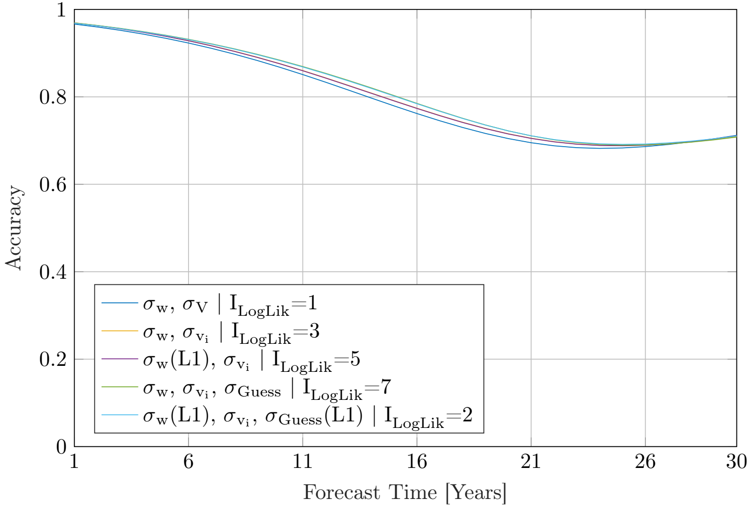

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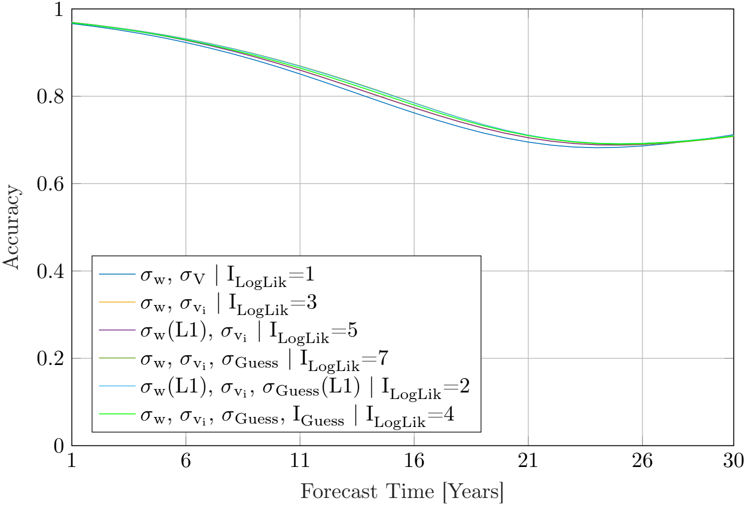

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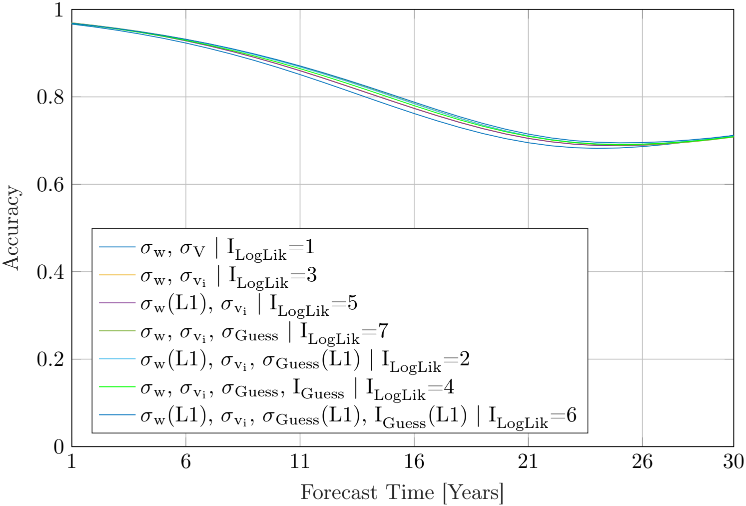
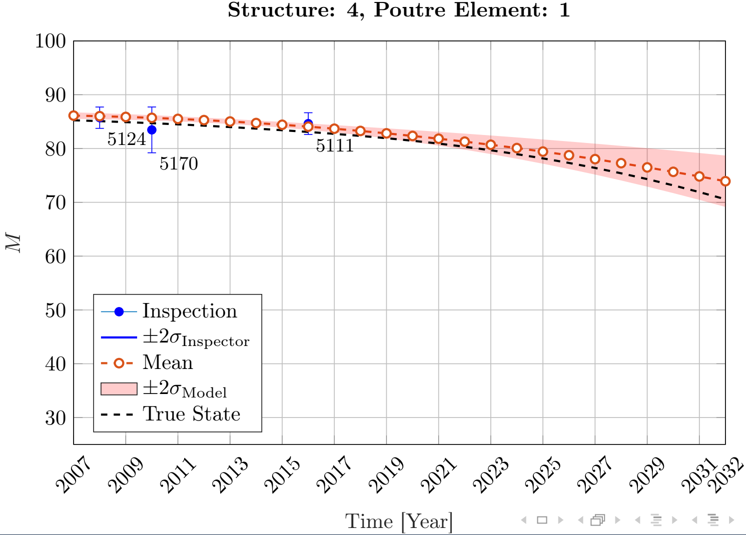
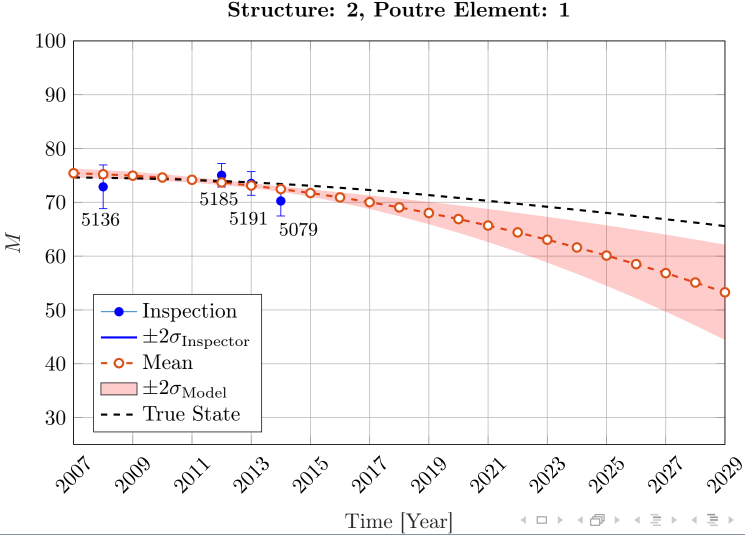


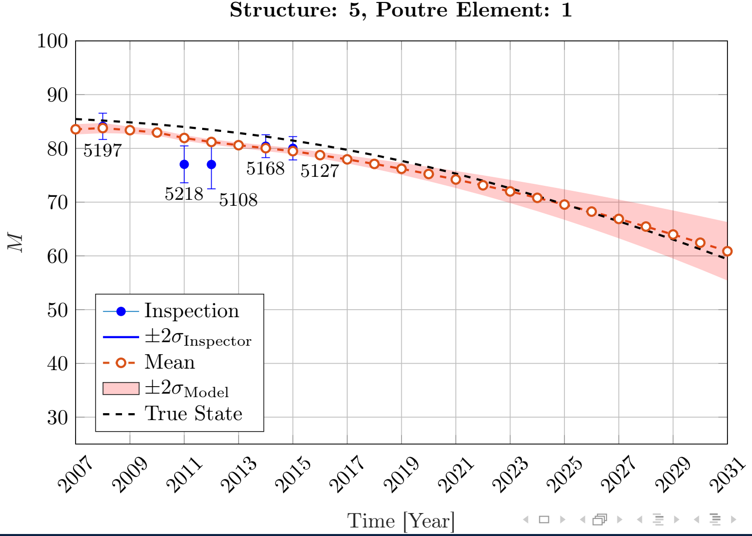
Perfect Estimation Case



Bad Estimation Case



An Average Estimation Case



Conclusions & Future Work

- Conclusions:
  1. Validation can be used to compare the performance of different forecast models.
  2. In some cases where the data is limited (small data sets), simulating the data characteristics can enable validating forecast models performance.

- Future Work:
  1. Panel Cross Validation with "real" visual inspection data.