A multimodel data assimilation framework for hydrology

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What is Data Assimilation ?

- Use observations to improve simulation

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- Use observations to improve simulation
- How ?
  - Kalman Filter
  - Variational method
  - **Particle Filter**
  - ...

Particle Filter

- In a perfect world
  - Identify most appropriate state variable values
  - Improve initial conditions
  - Better simulation & forecast

Particle Filter

- In a perfect world
  - Identify most appropriate state variable values
  - Improve initial conditions
  - Better simulation & forecast
- But life is not perfect...
  - Bias in the forcing
  - **Error in the model structure**

  $\Rightarrow$ Filter may fail

Error in model structure

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Multimodel approach

- No model is always better than others
- Cover different conceptualization
- Compensation of models errors

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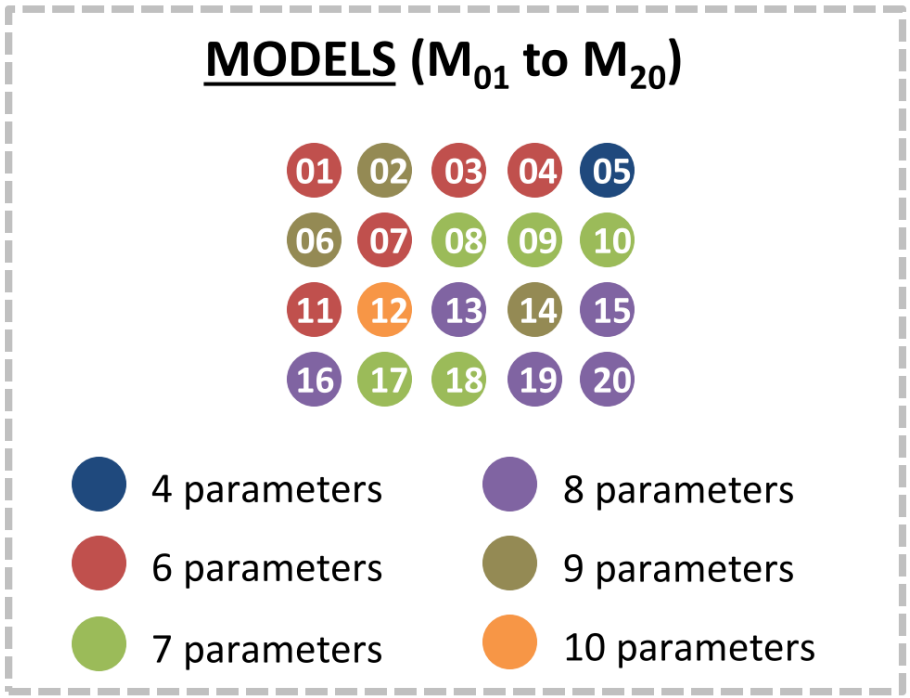

A multimodel data assimilation framework

Traditional Particle Filter **Multimodel Particle Filter**

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One model at a time	Update all models together

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One model at a time	Update all models together
Update model invididually	Make models cooperate during the assimilation
—	Foster compensation of models errors
—	Control multimodel predictive function
Require only one model	Require a large number of models ($\leqslant 20$)

Experimental set-up

- Comparison between individual and collective model updating

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  - Snow accumulation & spring freshet
  - 9-year period

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- Comparison between individual and collective model updating
- Catchments
  - 6 catchments in the Province of Québec
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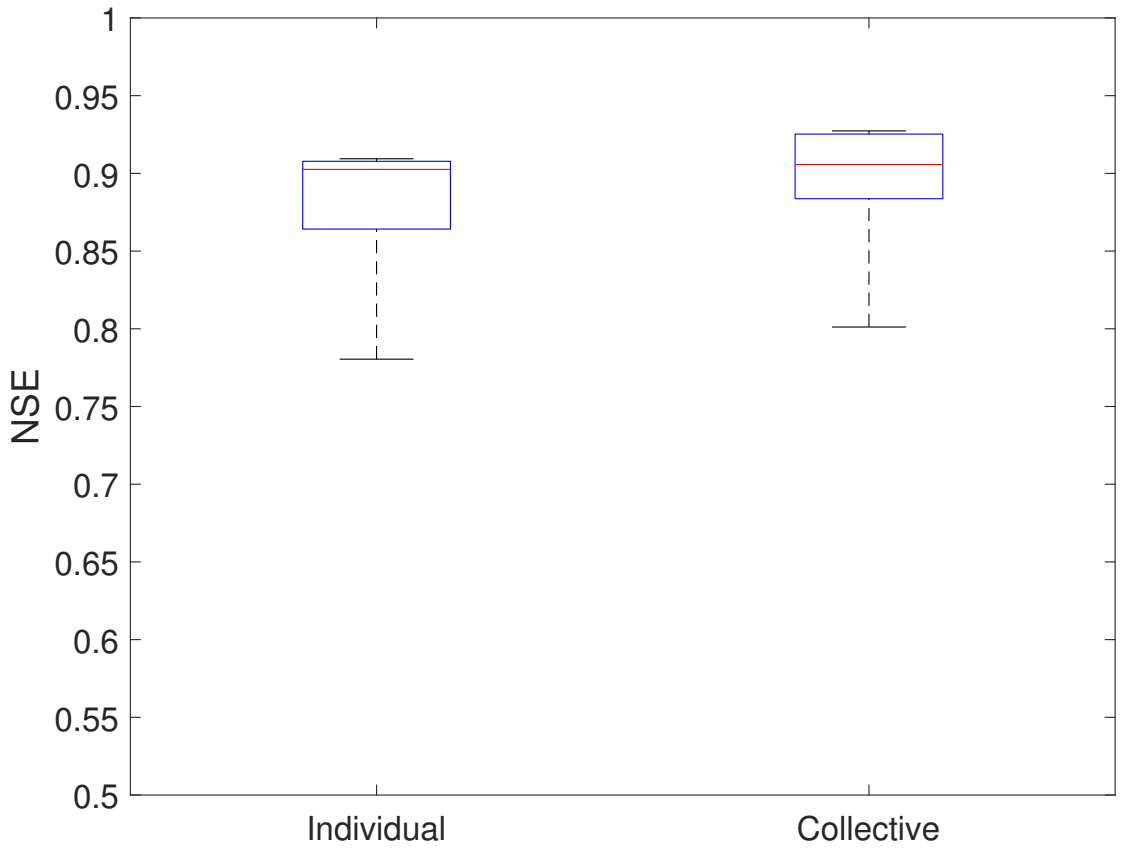
- Assessment of accuracy and reliability
  - Nash-Sutcliffe Efficiency (NSE)
  - Root mean square error (RMSE)
  - Continuous ranked probability score (CRPS)
  - Normalized root mean square error ratio (NRR)

Preliminary results



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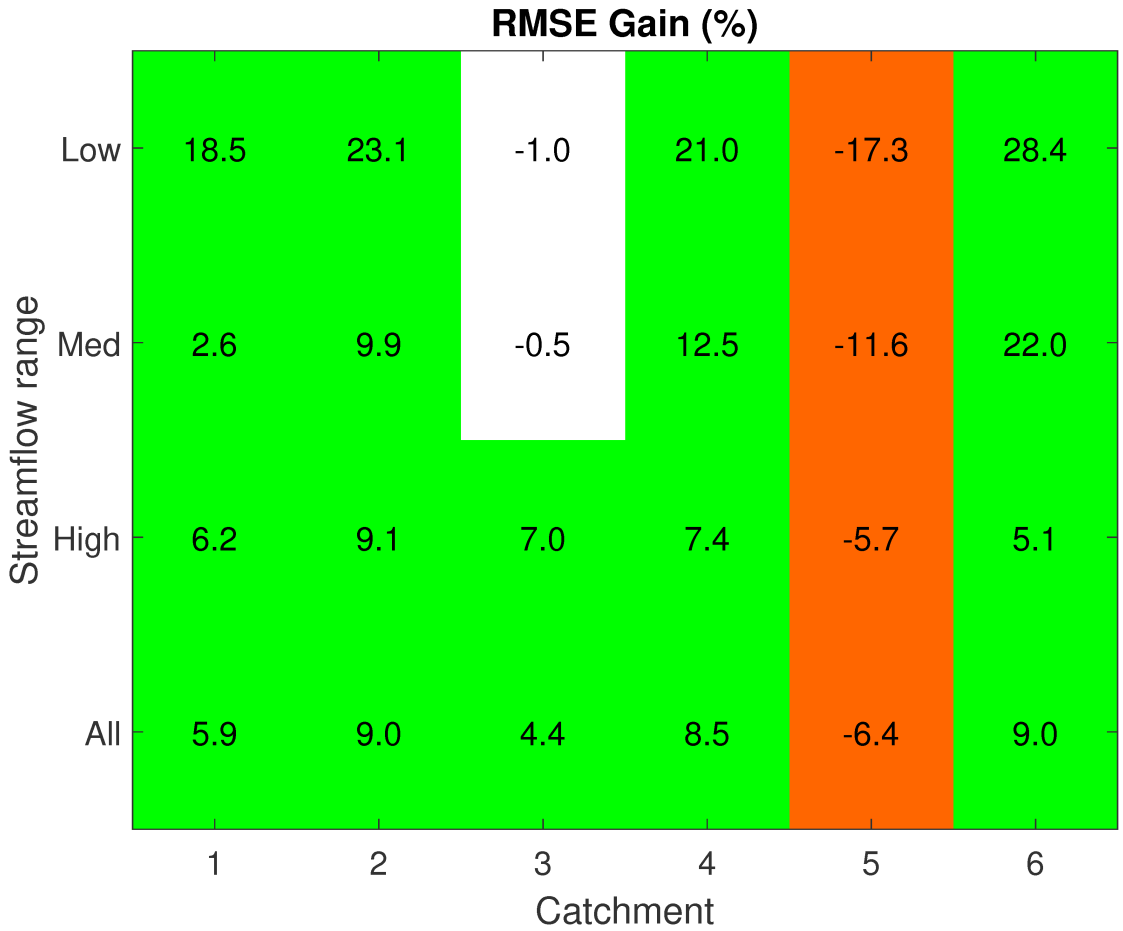
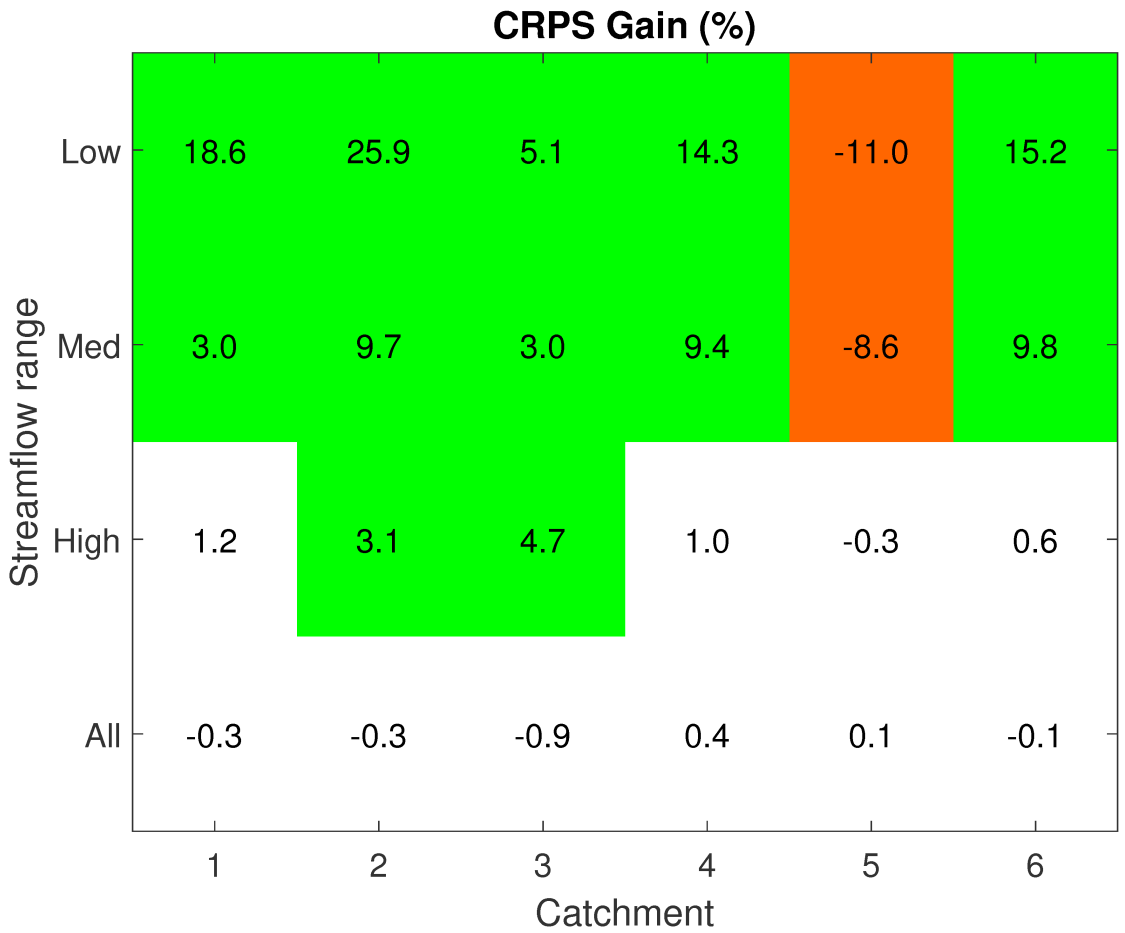


- ↗ Accuracy

Preliminary results



- ↗ Accuracy
- ↗ Resolution

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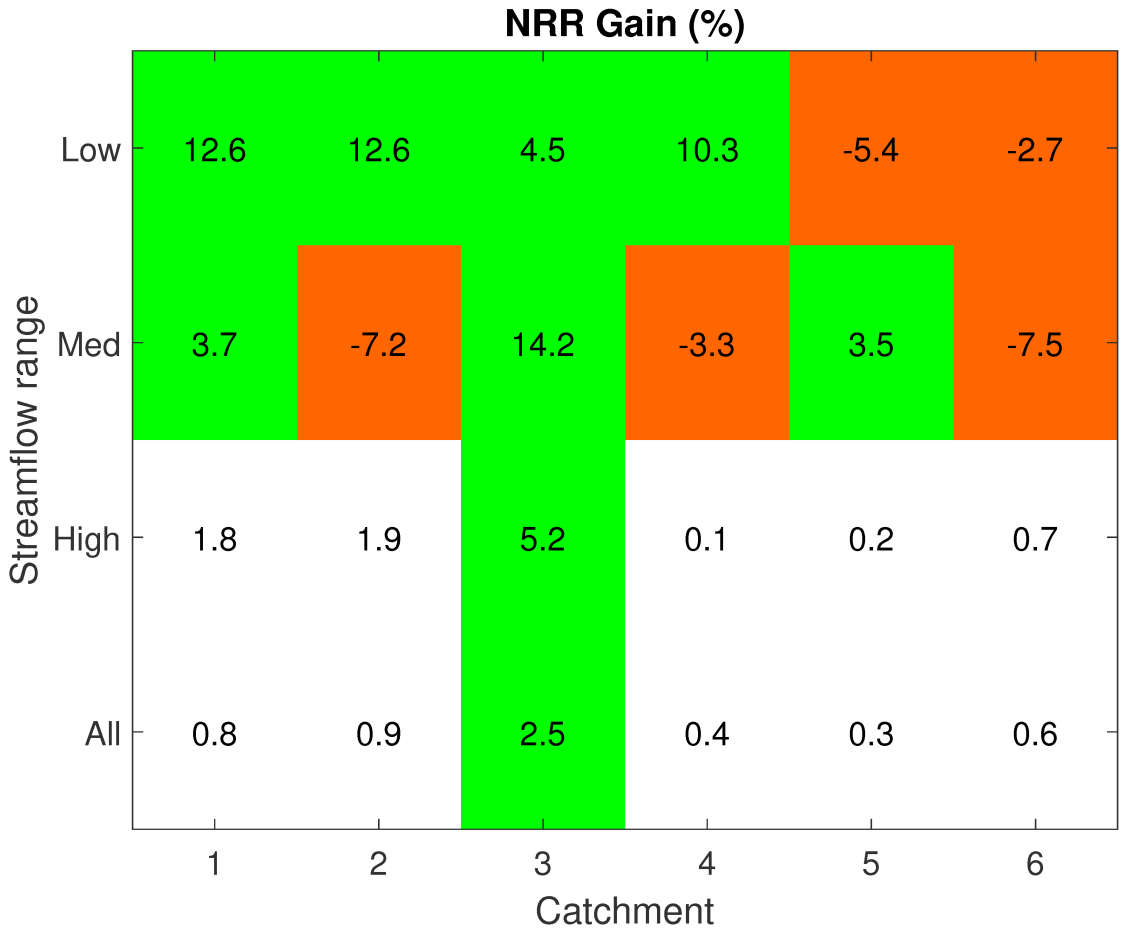


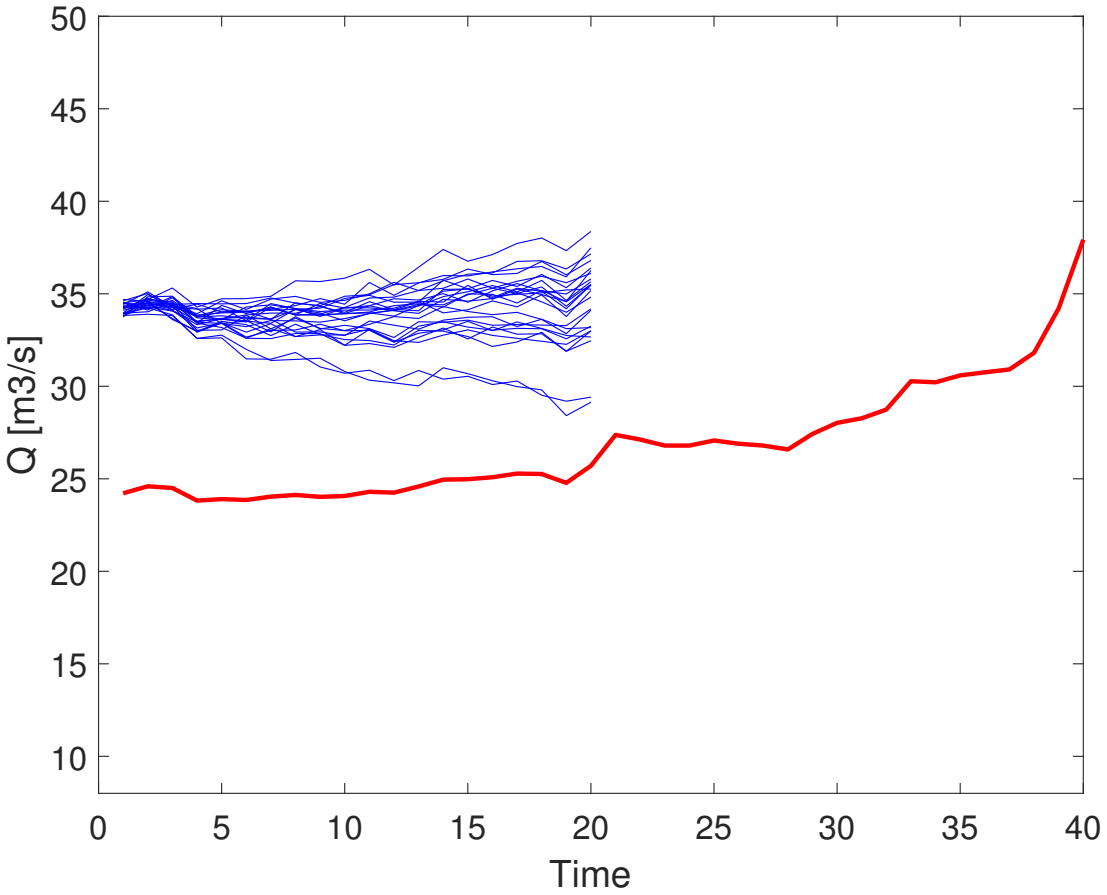
- ↗ Accuracy
- ↗ Resolution
- ≃ Reliability

Conclusion

A multimodel data assimilation framework

- Based on the particle filter
- Update models jointly in a cooperative mode
- Possible gain in accuracy and reliability

... Work in progress



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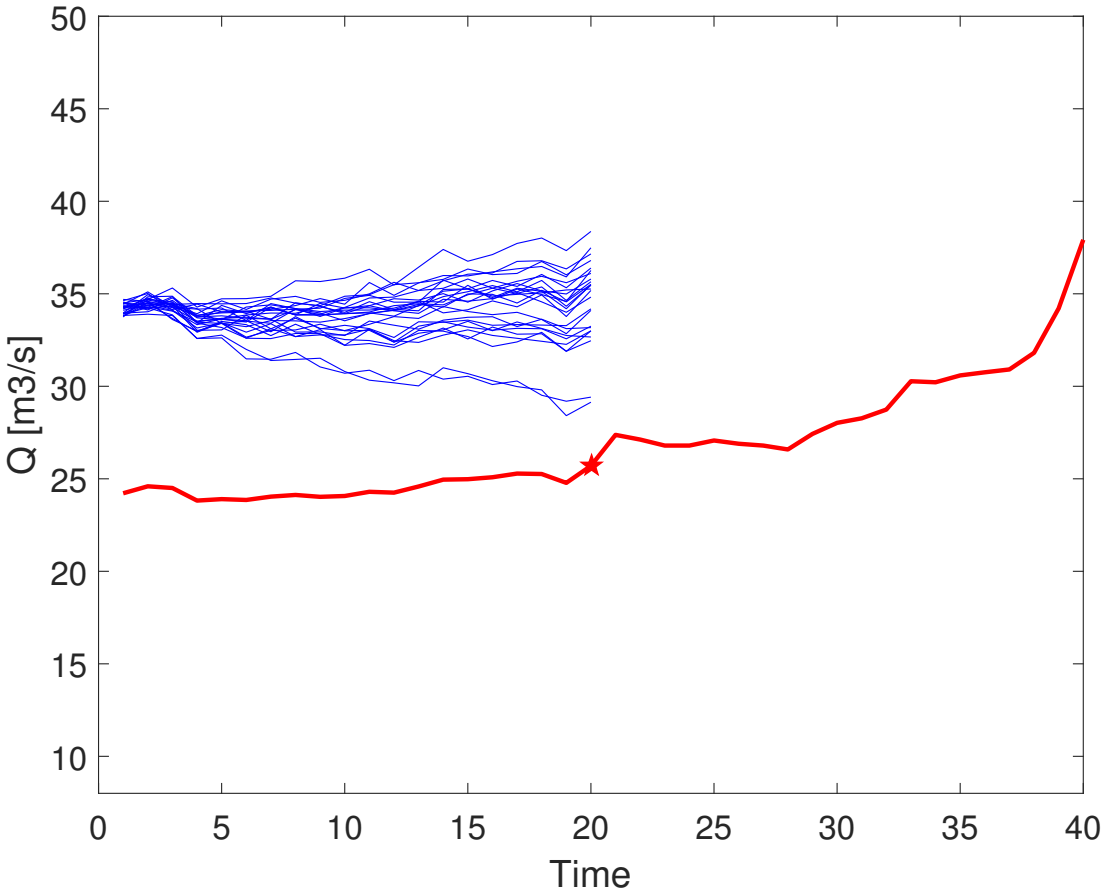

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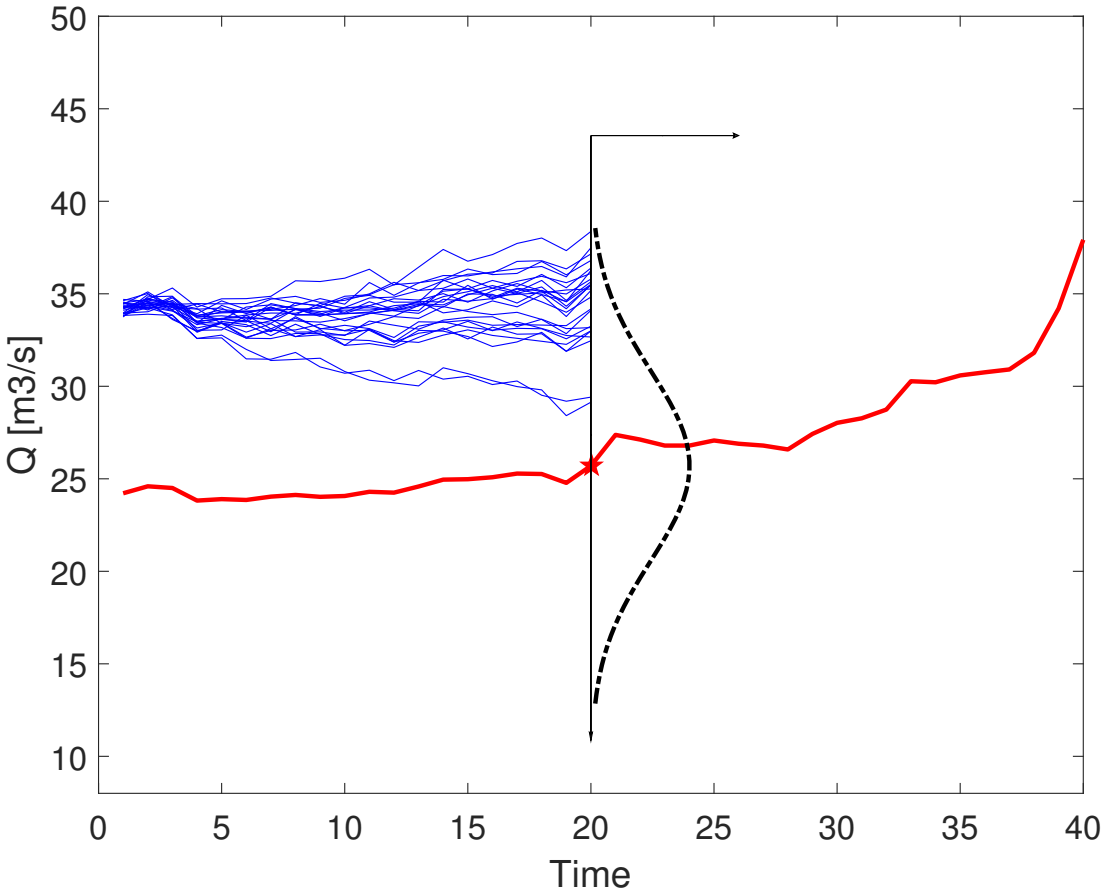

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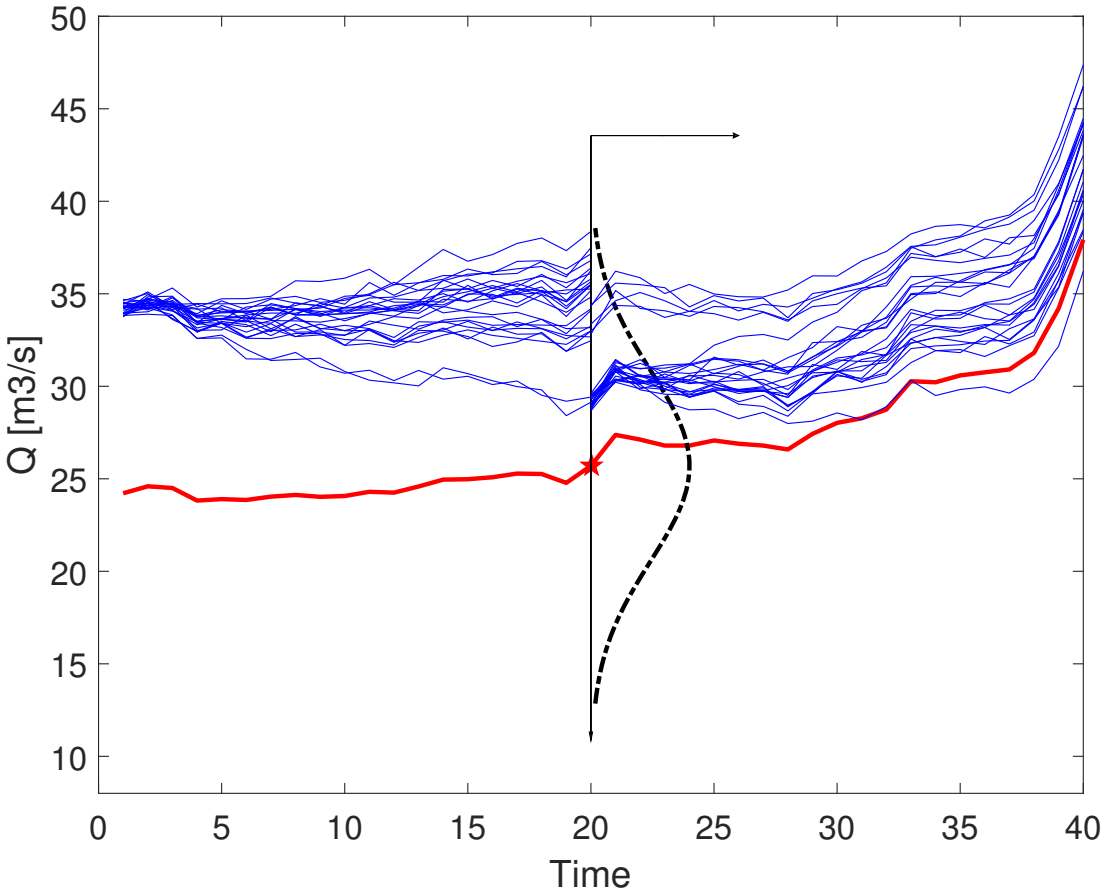
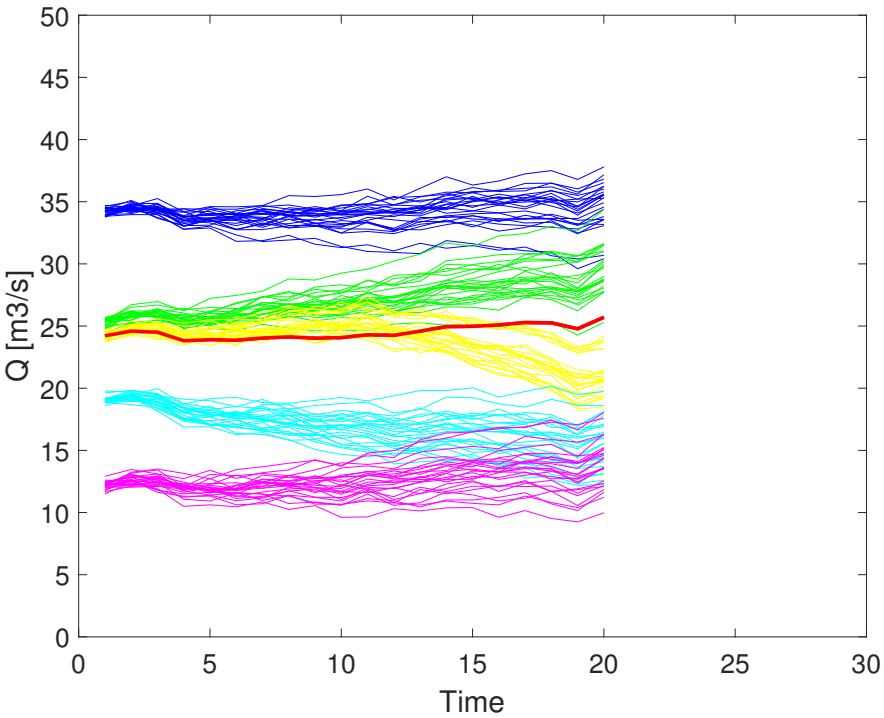
2. Compute particle weights based on their likelihood



1. Force model with perturbed inputs
2. Compute particle weights based on their likelihood
3. Resample
4. Iterate



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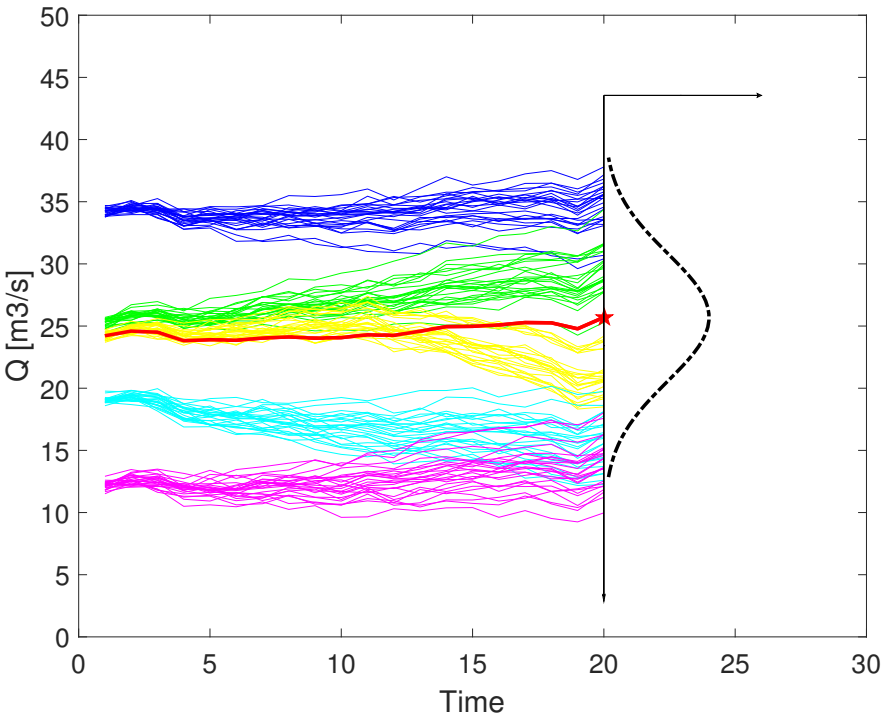

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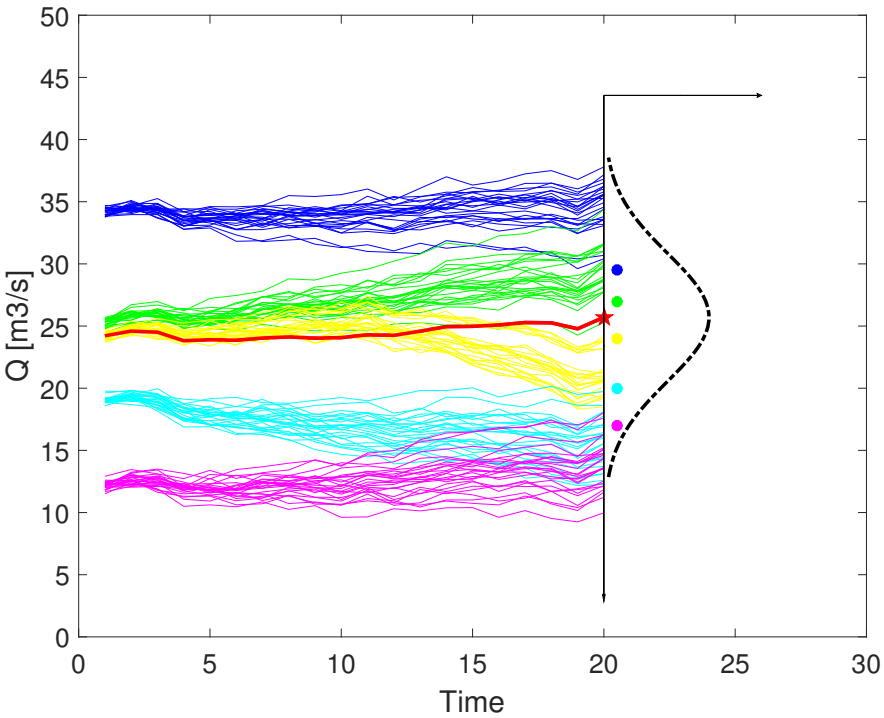

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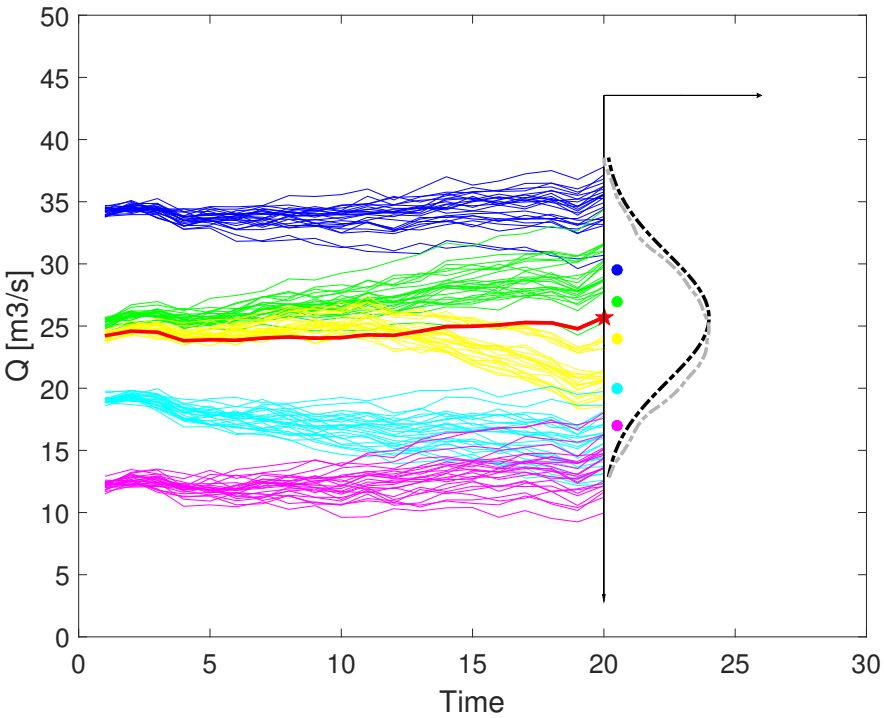

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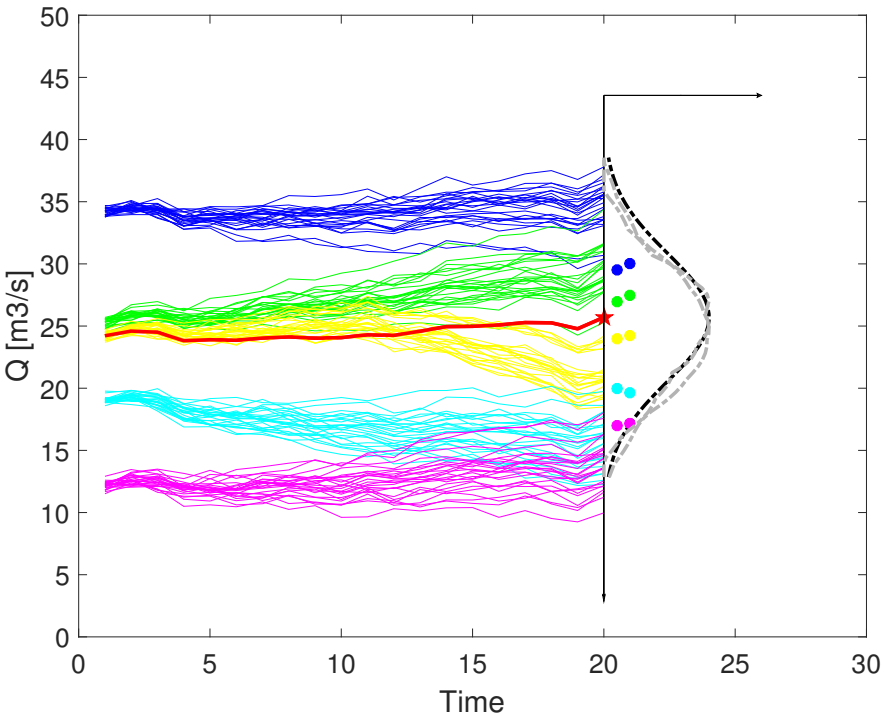

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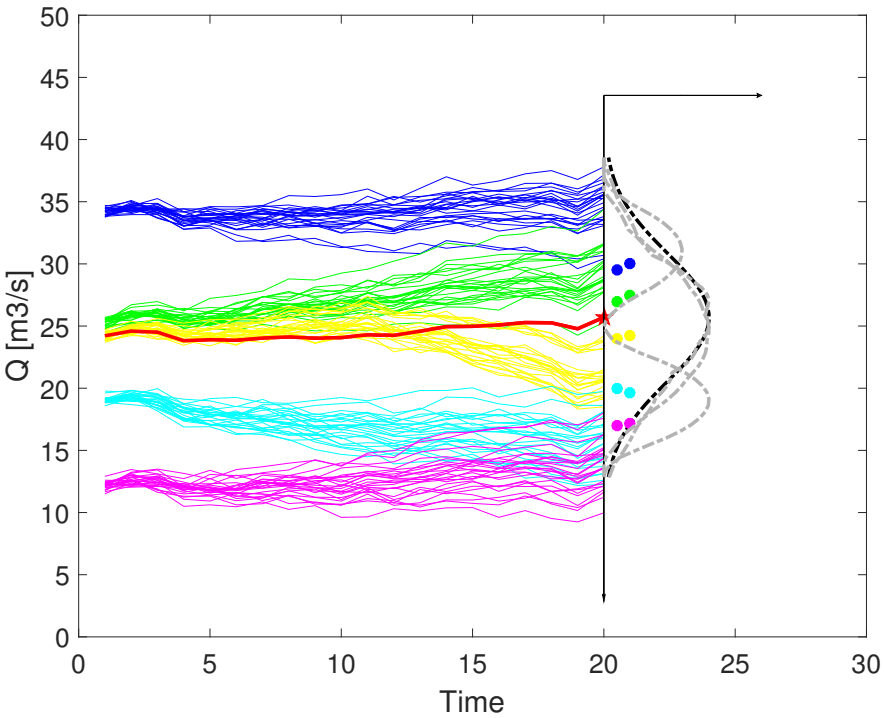

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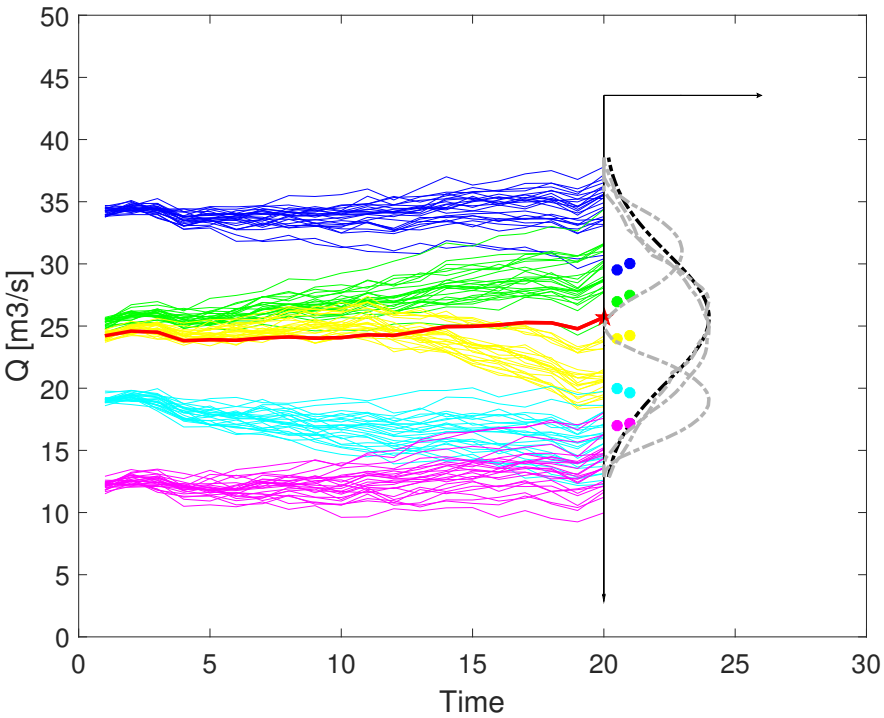

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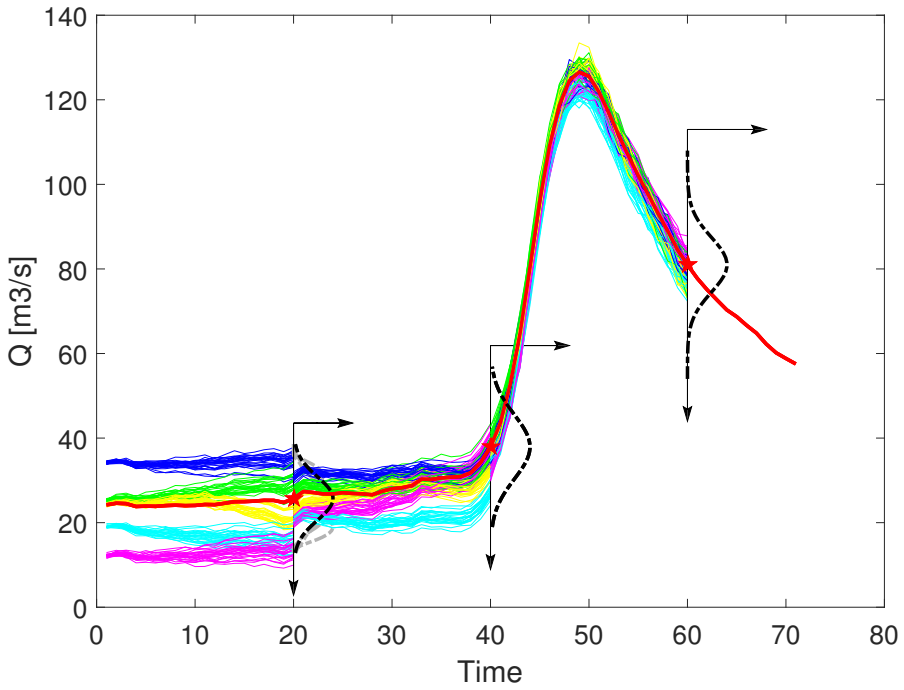

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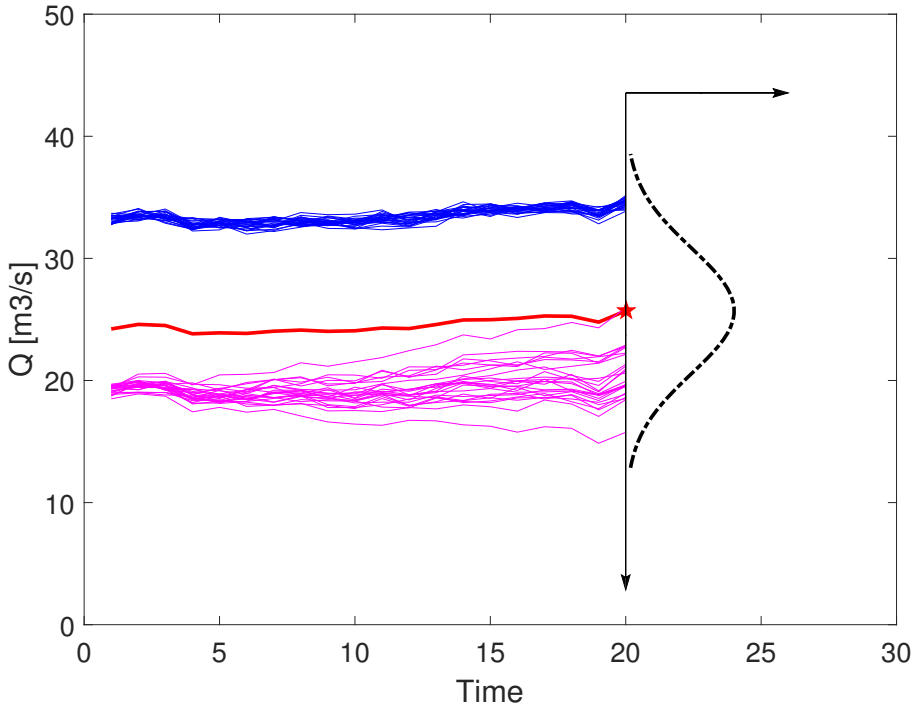
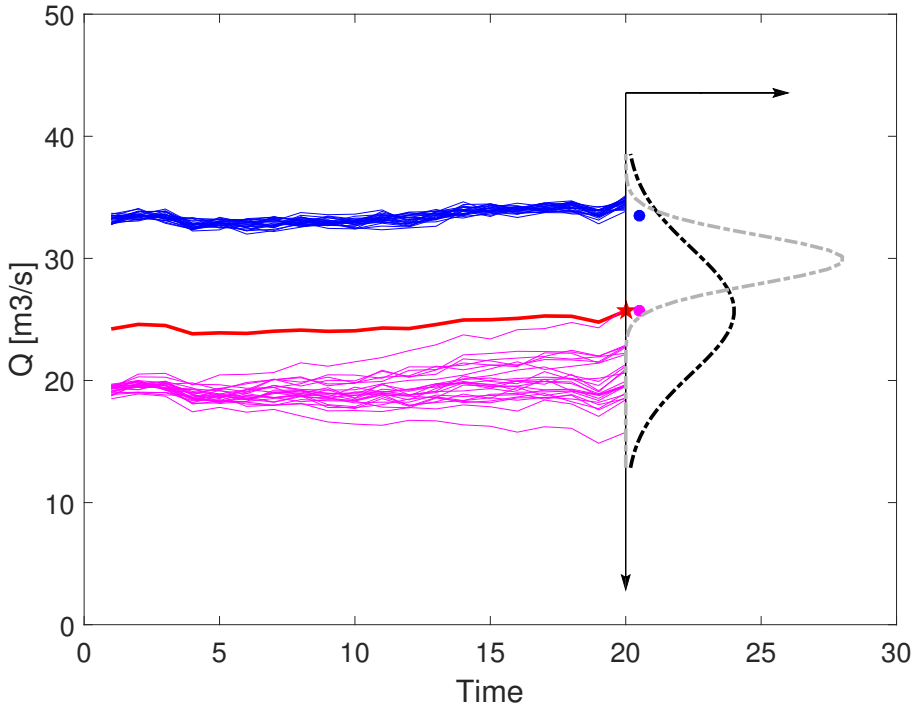


- Foster models error compensation
- Easier to explore predictive space
- May respect more model dynamic



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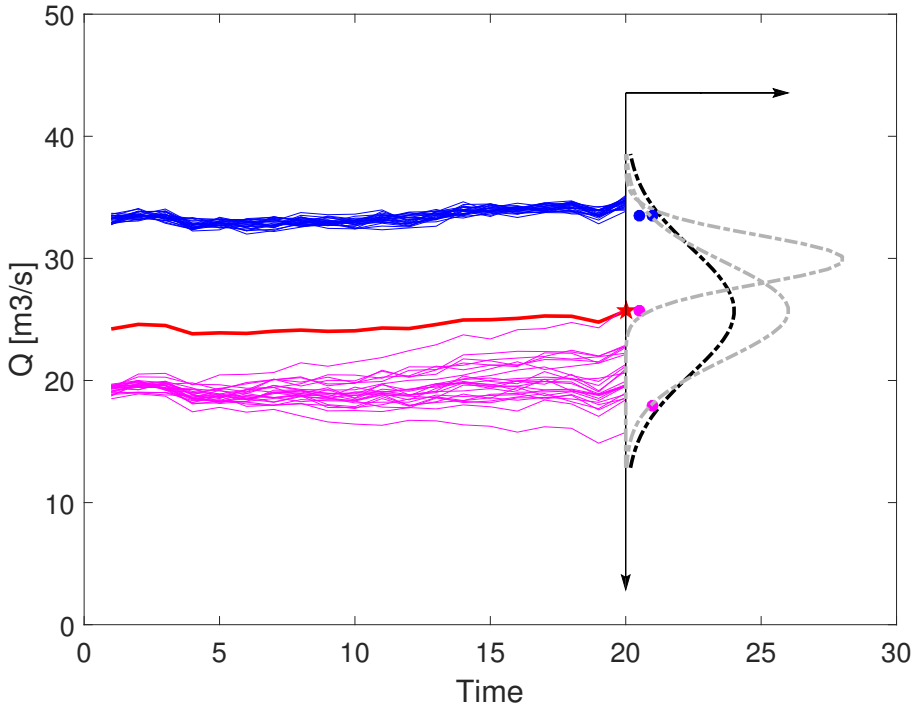

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