

The Ensemble Kalman Filter: Theoretical formulation and practical implementation

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The Ensemble Kalman Filter (EnKF)

- Represents error statistics using an ensemble of model states
- Evolves error statistics by ensemble integrations
- “Variance minimizing” analysis scheme operating on the ensemble



- Monte Carlo, low rank, error subspace method
- Converges to the Kalman Filter with increasing ensemble size
- Fully nonlinear error evolution, contrary to EKF
- Assumption of Gaussian statistics in analysis scheme

The error covariance matrix

Define ensemble covariances around the ensemble mean

$$\mathbf{P}^f \simeq \mathbf{P}_e^f = \overline{(\boldsymbol{\psi}^f - \overline{\boldsymbol{\psi}^f})(\boldsymbol{\psi}^f - \overline{\boldsymbol{\psi}^f})^T}$$

$$\mathbf{P}^a \simeq \mathbf{P}_e^a = \overline{(\boldsymbol{\psi}^a - \overline{\boldsymbol{\psi}^a})(\boldsymbol{\psi}^a - \overline{\boldsymbol{\psi}^a})^T}$$

- The ensemble mean $\overline{\boldsymbol{\psi}}$ is the best-guess.
- The ensemble spread defines the error variance.
- The covariance is determined by the smoothness of the ensemble members.
- A covariance matrix can be represented by an ensemble of model states (not unique).

Dynamical evolution of error statistics

- Each ensemble member evolve according to the model dynamics which is expressed by a stochastic differential equation

$$d\psi = \mathbf{f}(\psi)dt + \mathbf{g}(\psi)d\mathbf{q}.$$

- The probability density then evolve according to Kolmogorov's equation

$$\frac{\partial \phi}{\partial t} + \sum_i \frac{\partial (f_i \phi)}{\partial \psi_i} = \frac{1}{2} \sum_{i,j} \frac{\partial^2 \phi (\mathbf{g} \mathbf{Q} \mathbf{g}^T)_{ij}}{\partial \psi_i \partial \psi_j},$$

- This is the fundamental equation for evolution of error statistics and can be solved using Monte Carlo methods.

Analysis scheme (1)

- Given an ensemble of model forecasts ψ_j^f .
- Create an ensemble of observations

$$d_j = d + \epsilon_j,$$

with

- d the first guess observations,
- ϵ_j a vector of observation noise.
- The measurement error covariance matrix is

$$R \simeq R_e = \overline{\epsilon\epsilon^T}.$$

Analysis scheme (2)

- Update each ensemble member according to

$$\boldsymbol{\psi}_j^a = \boldsymbol{\psi}_j^f + K_e(\mathbf{d}_j - H\boldsymbol{\psi}_j^f).$$

where

$$K_e = P_e^f H^T (H P_e^f H^T + R_e)^{-1}$$

- This is equivalent to updating the mean

$$\overline{\boldsymbol{\psi}}^a = \overline{\boldsymbol{\psi}}^f + K_e(\mathbf{d} - H\overline{\boldsymbol{\psi}}^f).$$

- The posterior error covariance becomes

$$P_e^a = (\mathbf{I} - K_e H) P_e^f.$$

Analysis of the Analysis scheme (1)

- Define the ensemble matrix

$$\mathbf{A} = (\boldsymbol{\psi}_1, \boldsymbol{\psi}_2, \dots, \boldsymbol{\psi}_N) \in \mathfrak{R}^{n \times N}.$$

- The ensemble mean is (defining $\mathbf{1}_N \in \mathfrak{R}^{N \times N} \equiv 1/N$)

$$\bar{\mathbf{A}} = \mathbf{A}\mathbf{1}_N.$$

- The ensemble perturbations becomes

$$\mathbf{A}' = \mathbf{A} - \bar{\mathbf{A}} = \mathbf{A}(\mathbf{I} - \mathbf{1}_N).$$

- The ensemble covariance matrix $\mathbf{P}_e \in \mathfrak{R}^{n \times n}$ becomes

$$\mathbf{P}_e = \frac{\mathbf{A}'(\mathbf{A}')^T}{N - 1}$$

Analysis equation (2)

- Given a vector of measurements $\mathbf{d} \in \mathfrak{R}^m$, define

$$\mathbf{d}_j = \mathbf{d} + \boldsymbol{\epsilon}_j, \quad j = 1, \dots, N,$$

stored in

$$\mathbf{D} = (\mathbf{d}_1, \mathbf{d}_2, \dots, \mathbf{d}_N) \in \mathfrak{R}^{m \times N},$$

- The ensemble perturbations are stored in

$$\boldsymbol{\Upsilon} = (\boldsymbol{\epsilon}_1, \boldsymbol{\epsilon}_2, \dots, \boldsymbol{\epsilon}_N) \in \mathfrak{R}^{m \times N},$$

thus, the measurement error covariance matrix becomes

$$\mathbf{R}_e = \frac{\boldsymbol{\Upsilon} \boldsymbol{\Upsilon}^T}{N - 1}.$$

Analysis equation (3)

- The analysis equation can now be written

$$\mathbf{A}^a = \mathbf{A} + \mathbf{P}_e \mathbf{H}^T (\mathbf{H} \mathbf{P}_e \mathbf{H}^T + \mathbf{R}_e)^{-1} (\mathbf{D} - \mathbf{H} \mathbf{A}).$$

- Defining the innovations $\mathbf{D}' = \mathbf{D} - \mathbf{H} \mathbf{A}$ and using previous definitions:

$$\mathbf{A}^a = \mathbf{A} + \mathbf{A}' \mathbf{A}'^T \mathbf{H}^T \left(\mathbf{H} \mathbf{A}' \mathbf{A}'^T \mathbf{H}^T + \boldsymbol{\Upsilon} \boldsymbol{\Upsilon}^T \right)^{-1} \mathbf{D}'.$$

i.e., analysis expressed entirely in terms of the ensemble

Practical computation of analysis (1)

- Use pseudo inverse

$$HA'A'^T H^T + \Upsilon\Upsilon^T = Z\Lambda Z^T$$

$$(HA'A'^T H^T + \Upsilon\Upsilon^T)^{-1} = Z\Lambda^{-1}Z^T.$$

- Computational cost is:
 - $m^2 N$ to form $HA'A'^T H^T$,
 - $\mathcal{O}(m^2)$ for eigenvalue decomposition.
- Unaffordable for large m !

Practical computation of analysis (2)

- Note that $HA'\Upsilon^T \equiv 0$, thus

$$HA'A'^T H^T + \Upsilon\Upsilon^T = (HA' + \Upsilon)(HA' + \Upsilon)^T.$$

- Compute SVD, $HA' + \Upsilon = U\Sigma V^T$, giving

$$HA'A'^T H^T + \Upsilon\Upsilon^T = U\Sigma V^T V\Sigma^T U^T = U\Sigma\Sigma^T U^T.$$

- Computational cost is $\mathcal{O}(mN)$ for SVD.

Practical computation of analysis (3)

- The analysis equation can now be written

$$\mathbf{A}^a = \mathbf{A} + \mathbf{A}'(\mathbf{H}\mathbf{A}')^T \mathbf{U}\mathbf{\Lambda}^{-1}\mathbf{U}^T \mathbf{D}'.$$

- The computation goes as follows with $p \leq N$

$$\mathbf{X}_1 = \mathbf{\Lambda}^{-1}\mathbf{U}^T \quad \in \mathfrak{R}^{N \times m} \quad mp,$$

$$\mathbf{X}_2 = \mathbf{X}_1 \mathbf{D}' \quad \in \mathfrak{R}^{N \times N} \quad mNp,$$

$$\mathbf{X}_3 = \mathbf{U}\mathbf{X}_2 \quad \in \mathfrak{R}^{m \times N} \quad mNp,$$

$$\mathbf{X}_4 = (\mathbf{H}\mathbf{A}')^T \mathbf{X}_3 \quad \in \mathfrak{R}^{N \times N} \quad mNN,$$

$$\mathbf{A}^a = \mathbf{A} + \mathbf{A}'\mathbf{X}_4 \quad \in \mathfrak{R}^{n \times N} \quad nNN,$$

- All m^2N computations reduced to mN^2 .

Practical computation of analysis (4)

- The final update can be written as

$$\begin{aligned} \mathbf{A}^a &= \mathbf{A} + (\mathbf{A} - \overline{\mathbf{A}}) \mathbf{X}_4 \\ &= \mathbf{A} + \mathbf{A}(\mathbf{I} - \mathbf{1}_N) \mathbf{X}_4 \\ &= \mathbf{A}(\mathbf{I} + \mathbf{X}_4) \\ &= \mathbf{A} \mathbf{X}_5, \end{aligned}$$

thus, the analysis is a “weakly nonlinear combination” of the forecast ensemble.

- Note also

$$\begin{aligned} \mathbf{A}^a &= \mathbf{A} + \mathbf{P}_e \mathbf{H}^T (N - 1) \mathbf{X}_3 \\ &\equiv \mathbf{A} \mathbf{X}_5 \end{aligned}$$

Remarks on the analysis equation (1)

- Covariances only needed between observed variables at measurement locations.
- Covariances never computed but indirectly used to determine HPH^T .
- Analysis may be interpreted as:
 - combination of ensemble members, or,
 - forecast plus combination of covariance functions.
- Covariances only needed to compute X_5 .
- Accuracy of analysis is determined by
 - the accuracy of X_5
 - the properties of the ensemble error space

Remarks on the analysis equation (2)

- For a linear model, any choice of X_5 will result in an analysis which is also a solution of the model.
- Filtering of covariance functions introduces nondynamical modes in the analysis.

Local analysis

- A local analysis is computed grid point by grid point using only nearby measurements.
- Introduces nondynamical modes in the analysis.
- Different X_5 for each grid point.
- Allows us to reach a larger class of solutions.

Nonlinear measurements

- Measurement equation

$$d = \mathbf{h}(\boldsymbol{\psi}) + \boldsymbol{\epsilon}.$$

- Define ensemble of model prediction of the measurements

$$\hat{\mathbf{A}} = (\mathbf{h}(\boldsymbol{\psi}_1), \dots, \mathbf{h}(\boldsymbol{\psi}_N)), \in \mathfrak{R}^{\hat{m} \times N}.$$

- The analysis then becomes

$$\mathbf{A}^a = \mathbf{A} + \mathbf{A}' \hat{\mathbf{A}}'^T \left(\hat{\mathbf{A}}' \hat{\mathbf{A}}'^T + \boldsymbol{\Upsilon} \boldsymbol{\Upsilon}^T \right)^{-1} (\mathbf{D} - \hat{\mathbf{A}}),$$

- Analysis based on covariances between $\mathbf{h}(\boldsymbol{\psi})$ and $\boldsymbol{\psi}$.

Ensemble Kalman Smoother (EnKS)

- Starts with EnKF solution.
- Computes updates backward in time;
 - sequentially for each measurement time,
 - using covariances in time,
 - no backward integrations.
- The analysis becomes for $t_{i-1} \leq t' < t_i \leq t_k$:

$$\mathbf{A}_{\text{EnKS}}^{\text{a}}(t') = \mathbf{A}_{\text{EnKF}}(t') \prod_{j=i}^k \mathbf{X}_5(t_j)$$

Some recent applications of the EnKF

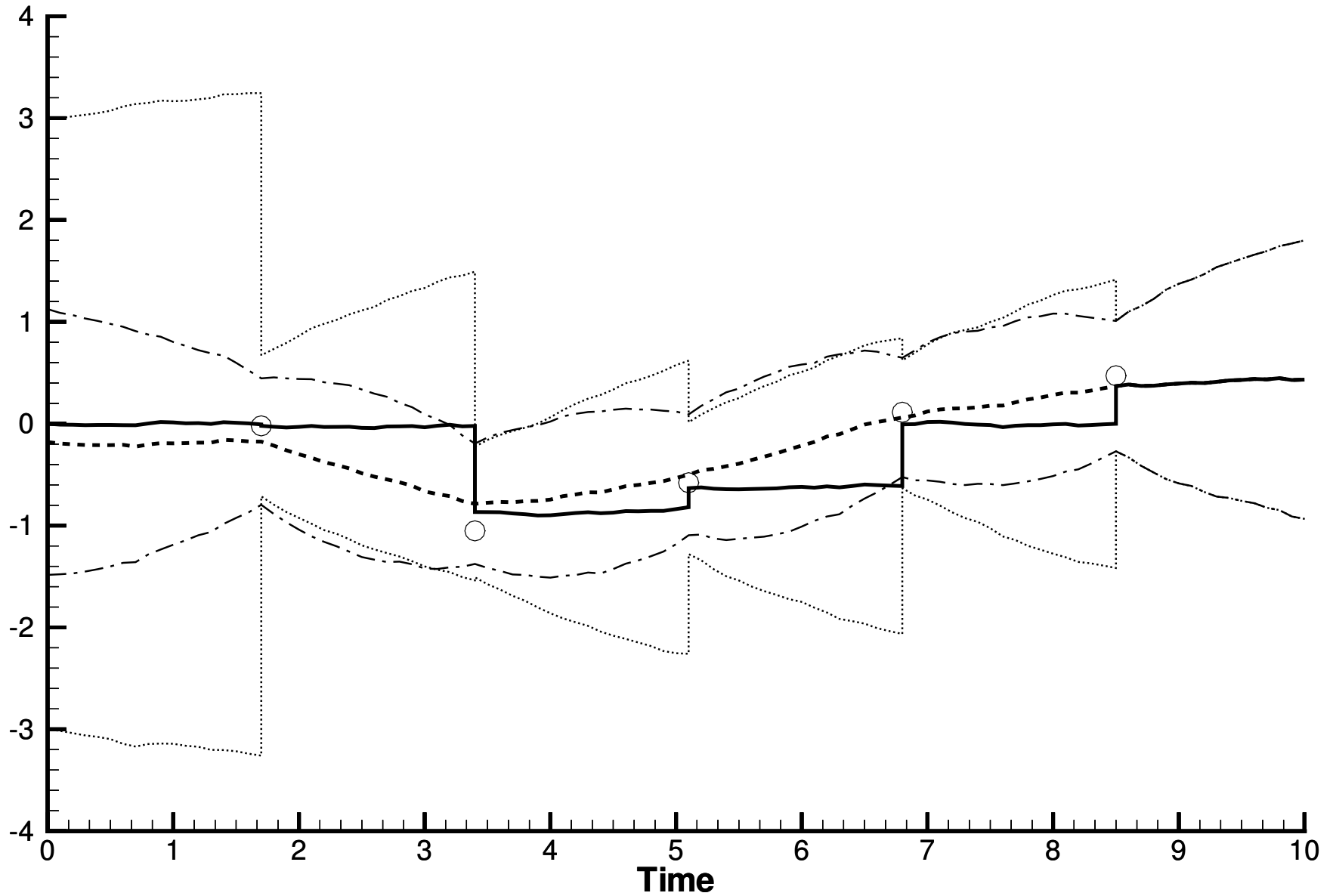
- Haugan and Evensen (2002), Ocean Dynamics.
- Mitchell et al. (2002), MWR.
- Brusdal et al (2003), JMS.
- Natvik and Evensen (2003a,b), JMS.
- Keppenne and Rienecker (2003), JMS.
- DIADEM project
- TOPAZ project (topaz.nersc.no)
- MERSEA project

Time correlated model noise

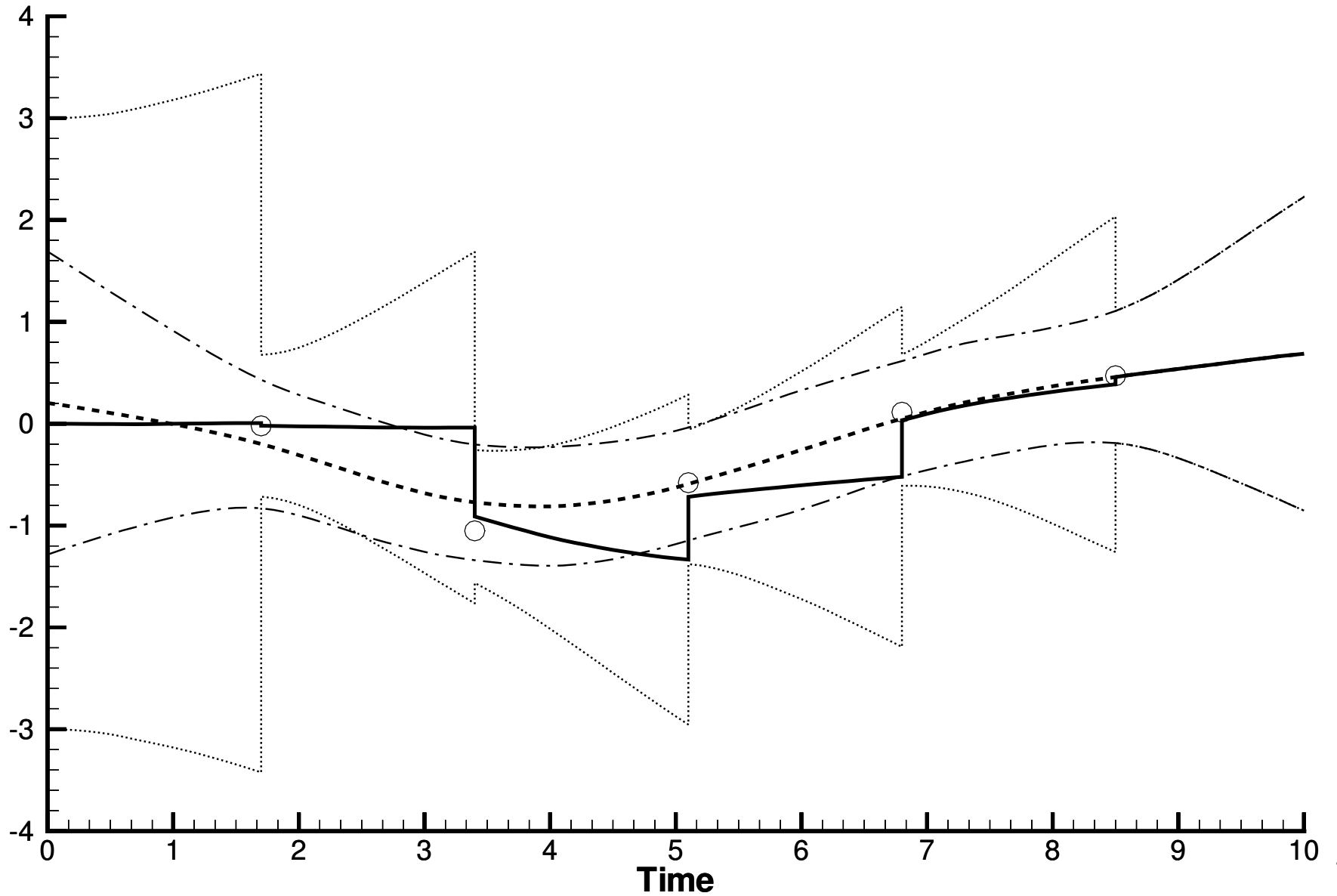
- Scalar model

$$\begin{pmatrix} q_k \\ \psi_k \end{pmatrix} = \begin{pmatrix} \alpha q_{k-1} \\ \psi_{k-1} + \sqrt{\Delta t} \sigma \rho q_k \end{pmatrix} + \begin{pmatrix} \sqrt{1 - \alpha^2} w_{k-1} \\ 0 \end{pmatrix}.$$

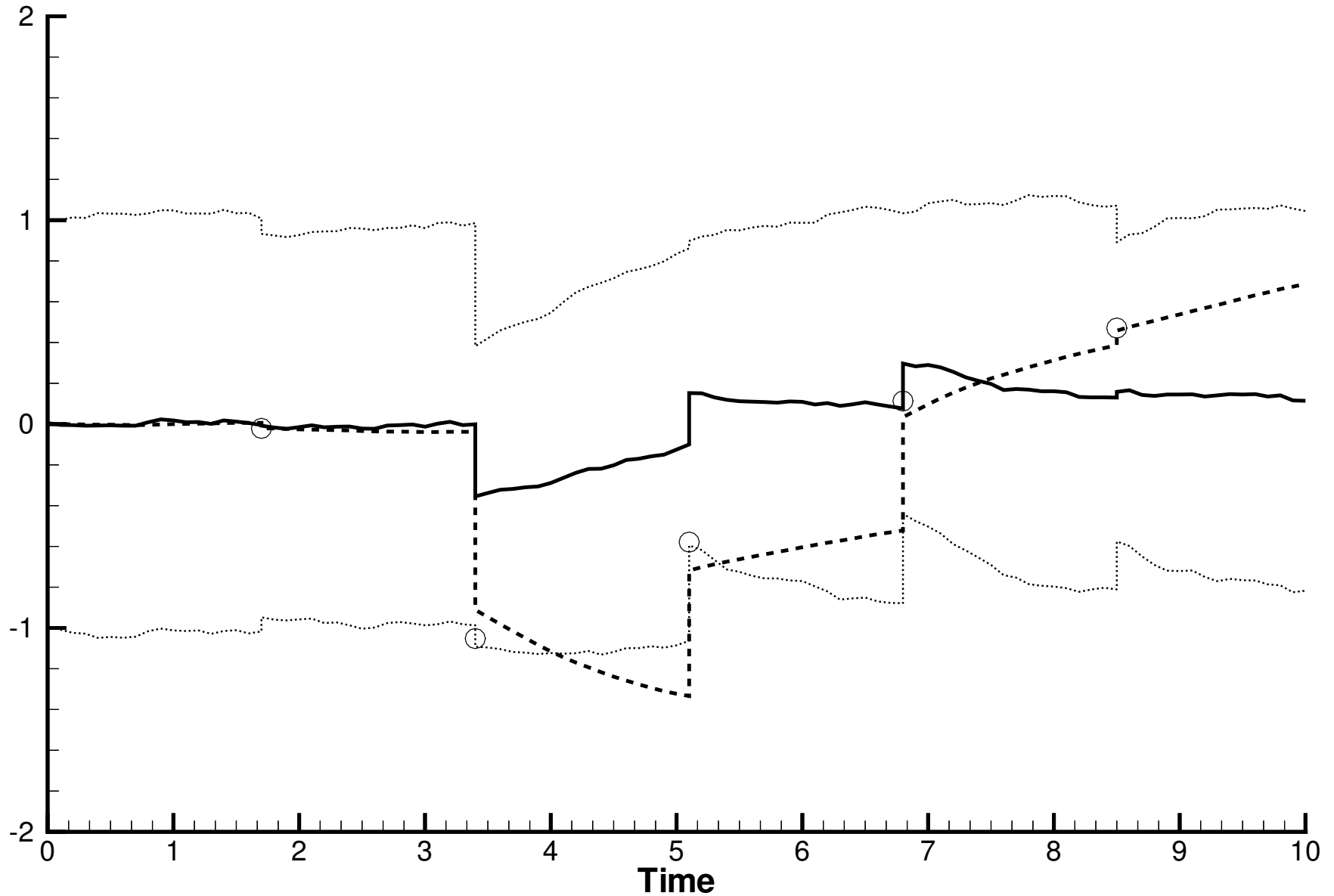
Results ($\alpha = 0$)



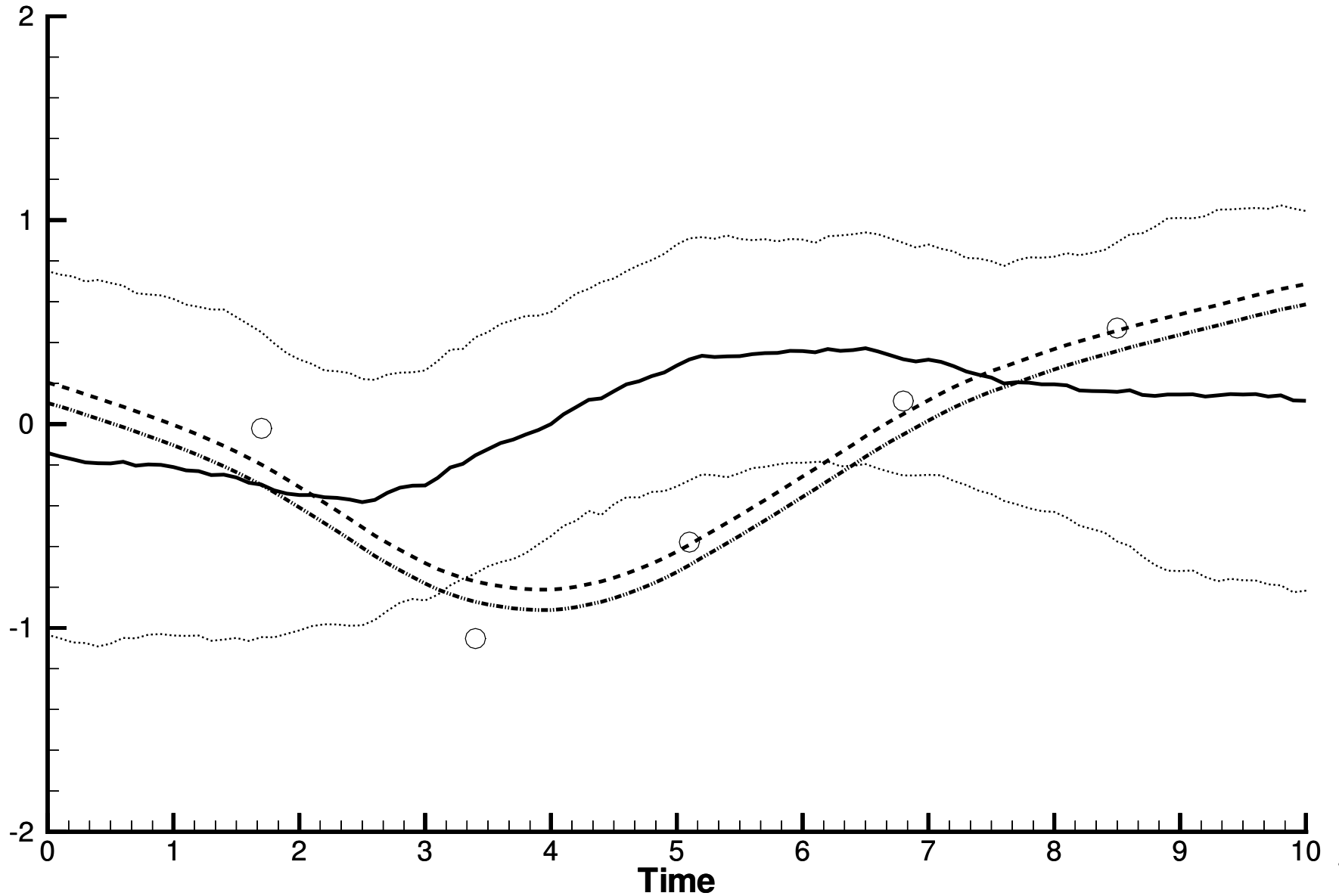
Results ($\alpha = 0.95$)



Estimate of model noise, EnKF



Estimate of model noise, EnKS



Model forced by estimated model error

$$\psi_k = \psi_{k-1} + \sqrt{\Delta t} \sigma \rho \hat{q}_k$$

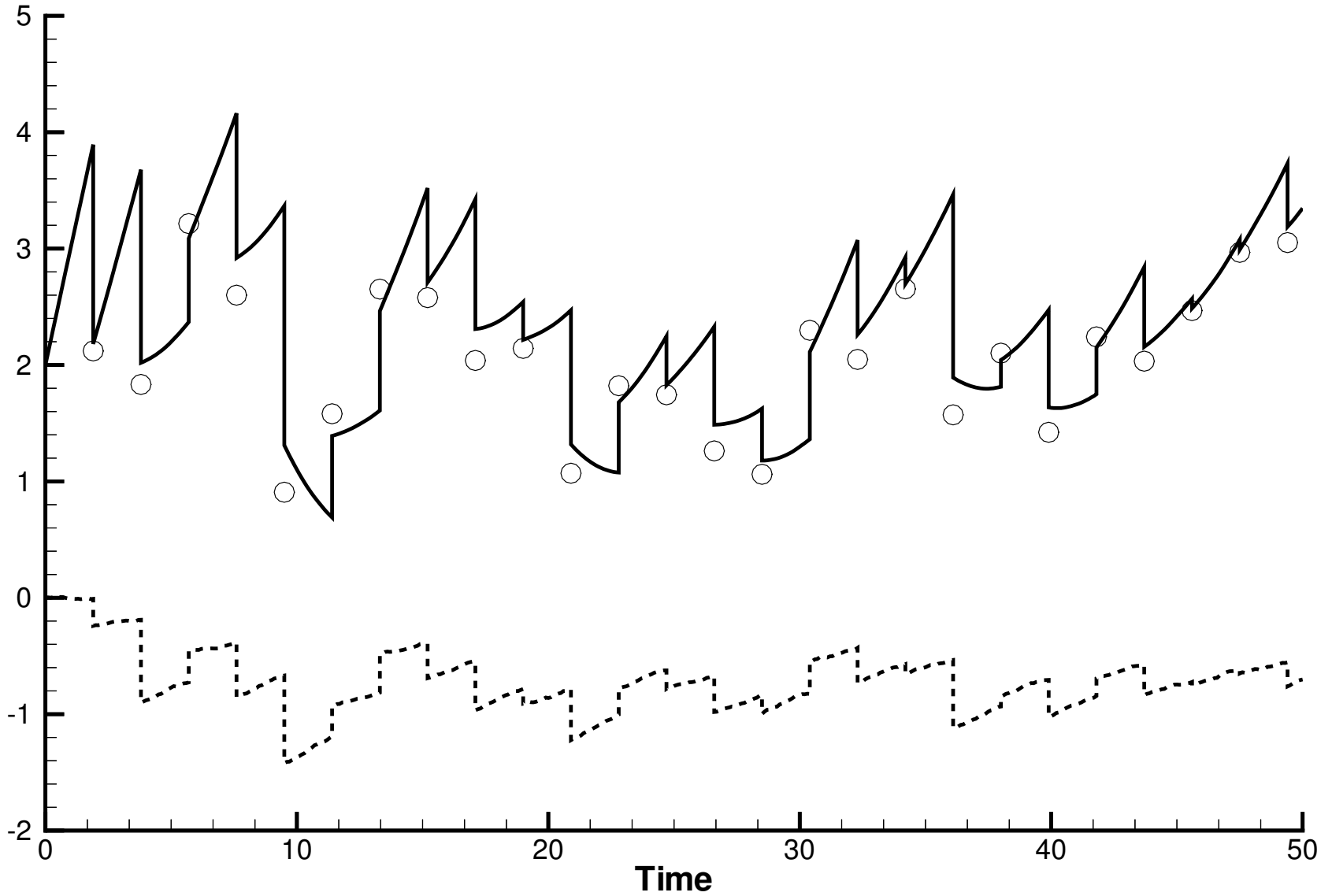
$$\psi_0 = \hat{\psi}_0$$

Parameter and bias estimation

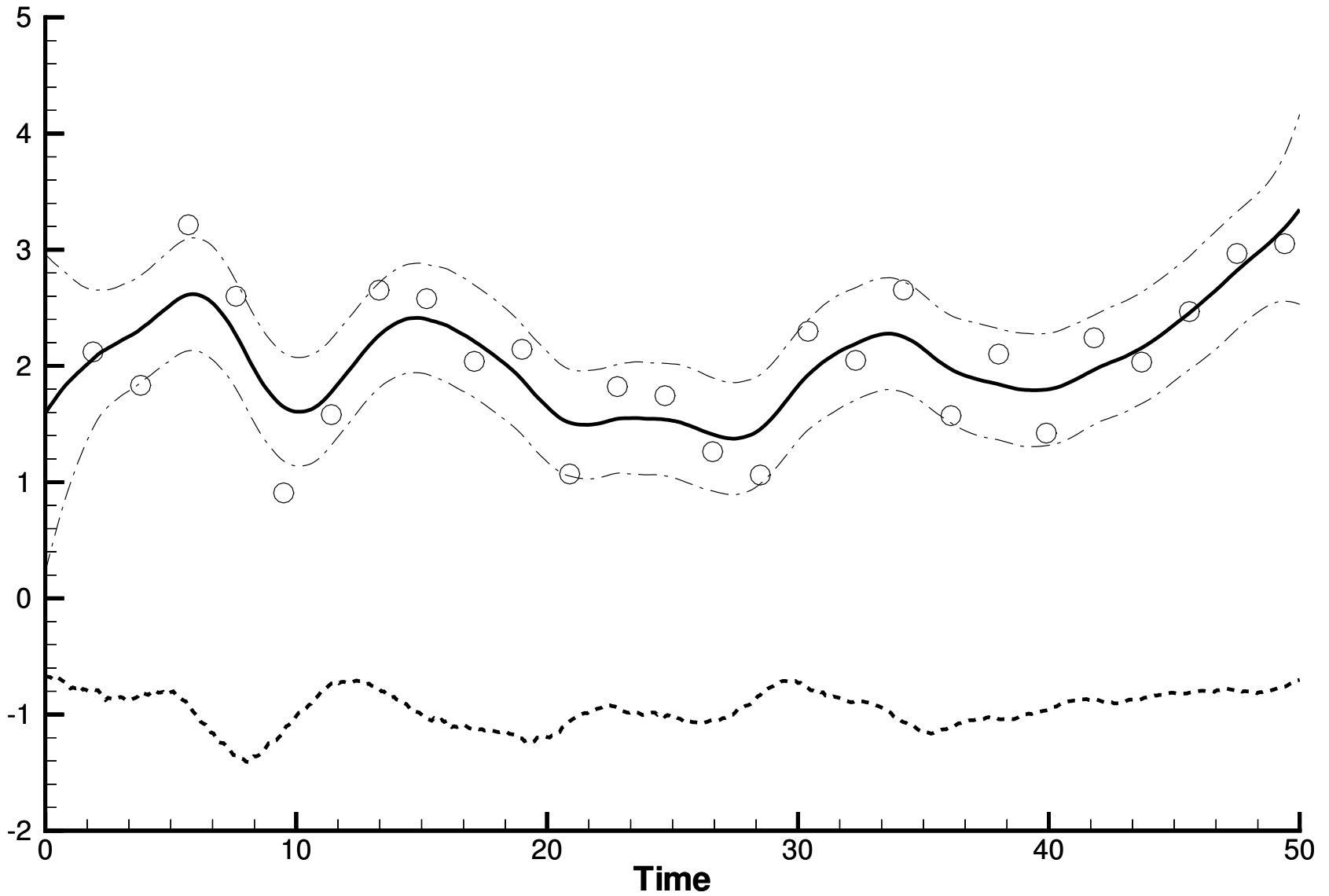
- Introduces poorly known parameter β_k in model

$$\begin{pmatrix} q_k \\ \beta_k \\ \psi_k \end{pmatrix} = \begin{pmatrix} \alpha q_{k-1} \\ \beta_{k-1} \\ \psi_{k-1} + (\eta + \beta_k)\Delta t + \sqrt{\Delta t}\sigma\rho q_k \end{pmatrix} + \begin{pmatrix} \sqrt{1 - \alpha^2}w_{k-1} \\ 0 \\ 0 \end{pmatrix}.$$

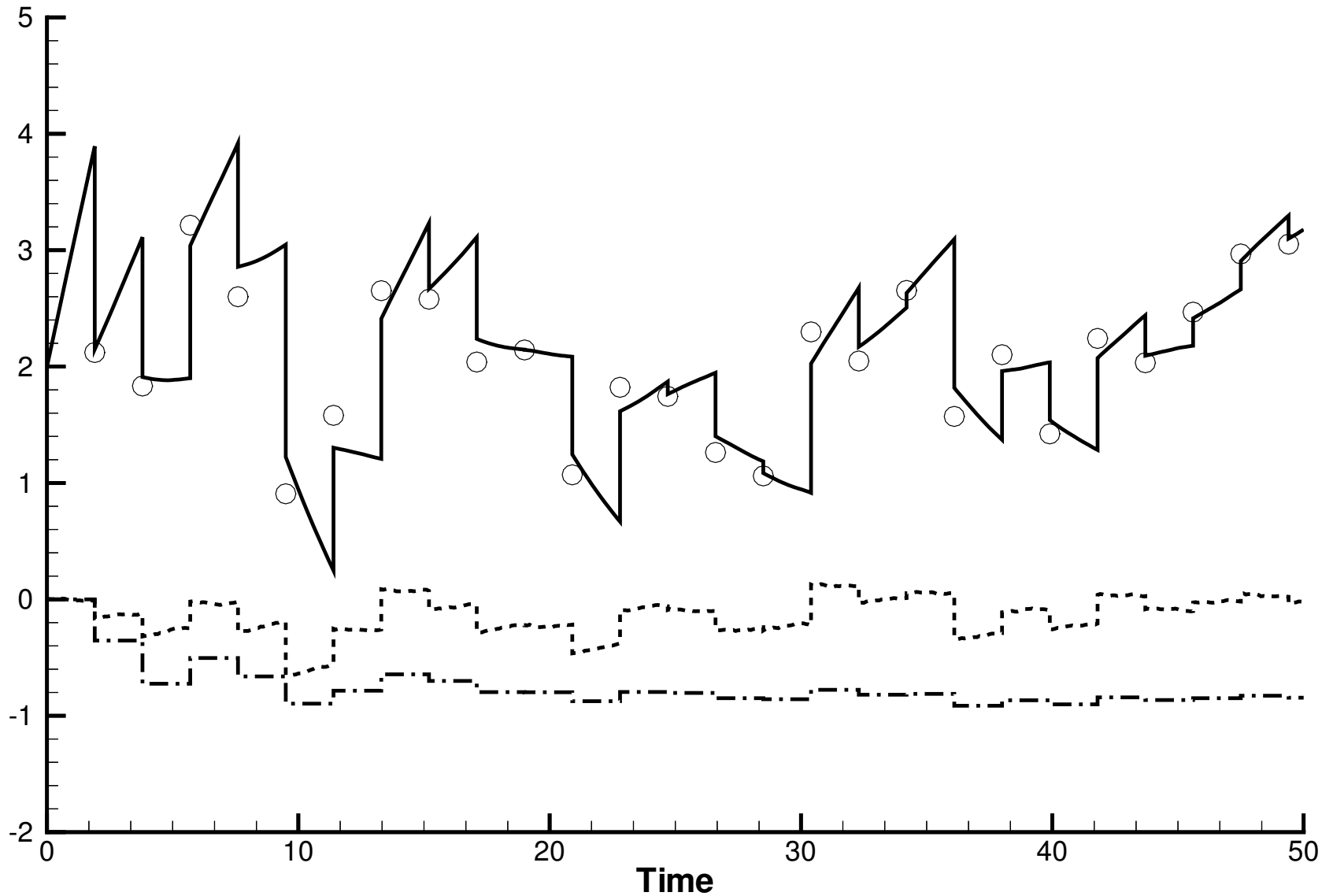
Estimate and model error, EnKF



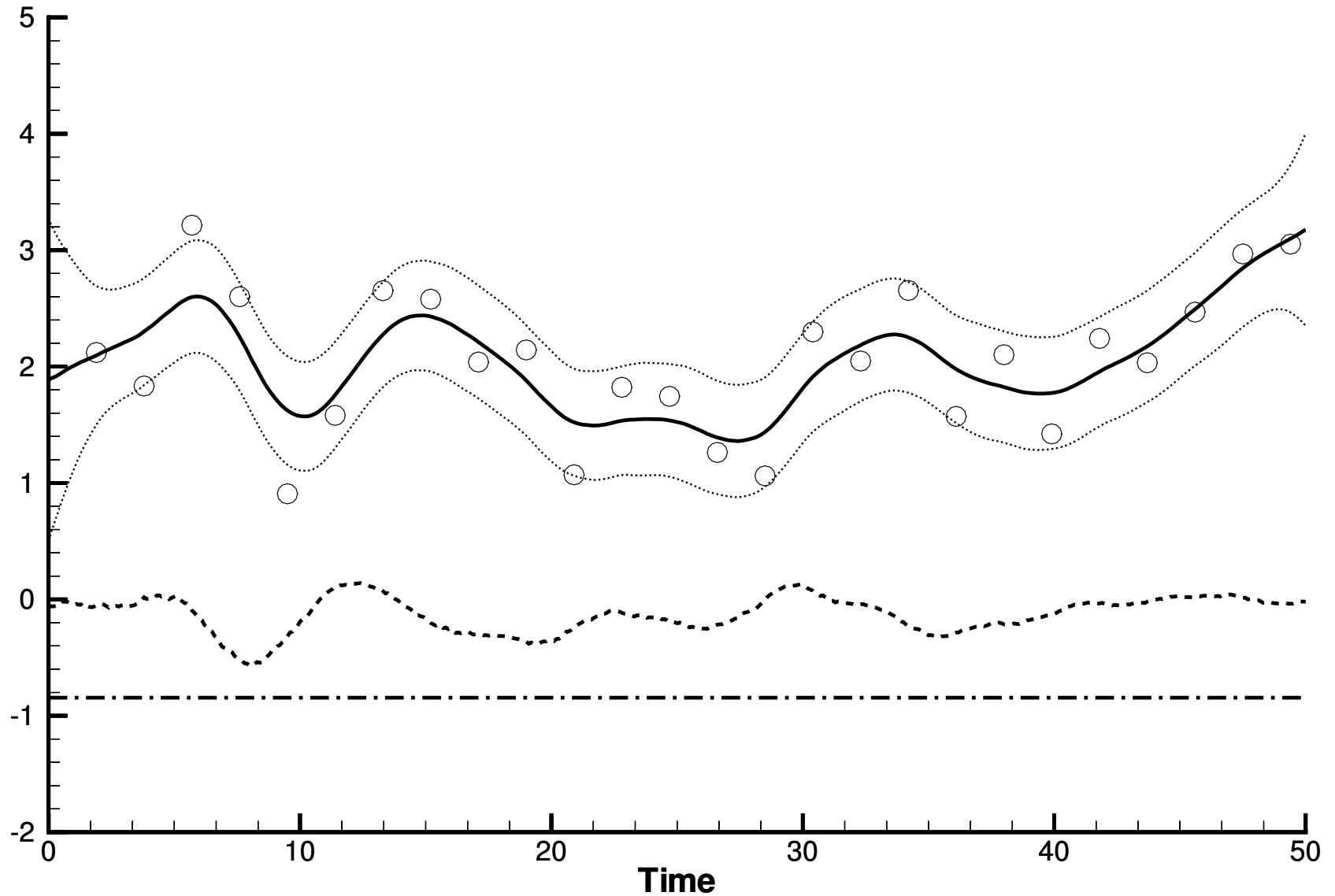
Estimate and model error, EnKS



Estimate, model error and bias, EnKF



Estimate, model error and bias, EnKS



Estimated bias and std dev

