Initially this type of simple RLC sensor actually appears to be problematic.

- Pervasive noise physically co-resident with the sensor
- System identification complications
- Sensitivity to sensor parasitic elements

With an unknown input estimator the input to the system, in this context the beam current, is modeled as a disturbance $d(t)$:
\[ \dot{x}(t) = Ax(t) + Bu(t) + d(t) \]
\[ y(t) = Cx(t) + Du(t) + e(t) \]
\[ e(t) \text{ is a disturbance scaling matrix} \]
\[ E \text{ is an output scaling matrix} \]
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The Octave pole placement invariant matrices $F$, $K$, and $H$:

To complete the estimator we need to derive time invariant matrices $F$, $K$, and $H$.

With conventional Kalman Filter design states become incoherent given the input error, being known in the state vector but the input error is not.

The mean square error is:
\[ E\{e(t)^2\} = E\{y(t)^2\} - E\{u(t)^2\} \]

\[ \text{The state vector can be calculated as } x(t) = E\{x(t)\} \]

The state vector converges recursively with $E\{x(t)\} \rightarrow x(t) \text{ as } t \rightarrow \infty \]

The Kalman Filter is a famous model-based state-estimator algorithm providing optimized iterative estimates of the unknown disturbance and that the estimation process can be decoupled from the system state estimates using an auxiliary estimator algorithm, the so-called Kalman Filter.

Any linear time-invariant multi-input multi-output system might be represented in a so-called state-space form:
\[ \dot{x}(t) = Ax(t) + Bu(t) + d(t) \]
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The optimized $K$ matrix for the Kalman filter is designed when solving the Algebraic Riccati Equation.

The Kalman filter computes an estimate of the state vector $\hat{x}_k$ at the present time $t_k$ on the basis of past measurements received up to the present time as
\[ \hat{x}_k = F\tilde{x}_{k-1} + K_k(y_k - C\tilde{x}_{k-1}) \]

\[ \text{Where:} \]
\[ F \text{ is the state transition matrix} \]
\[ K_k \text{ is the gain matrix} \]
\[ C \text{ is the output matrix} \]
\[ R \text{ is the input noise covariance} \]
\[ Q \text{ is the state noise covariance} \]
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For a linear system:
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- Initial results appear to indicate that we could do more to eliminate droop
- At this time, mismatching the UIE's knowledge of the target sensor
- Considering a novel approach for beam current transformer data acquisition was
- Obtaining sufficient observability for the beam current transformer sensor system simulated output.
- Estimator performance for the beam current transformer sensor systems.
- Simulation Results
- A passive pulsed-beam current transformer has a parallel RLC simplified equivalent circuit with a band-pass behavior transfer function and that the estimation process can be decoupled from the system state estimates using an auxiliary estimator algorithm, the so-called Kalman Filter.

Beam Current Transformer Challenges

- Initially this type of simple RLC sensor actually appears to be problematic
- Pervasive noise physically co-resident with the sensor
- System identification complications
- Sensitivity to sensor parasitic elements

Simplified Beam Current Transformer Circuit Model

- A passive pulsed-beam current transformer has a parallel RLC simplified equivalent circuit with a band-pass behavior transfer function
- There are two system internal states

Kalman Estimator Applicability

- Initially this type of simple RLC sensor actually appears to be problematic
- Pervasive noise physically co-resident with the sensor
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Conclusions

- After designing the estimator, the next step is to produce an estimation of the unknown disturbance in a suitable form, and test the estimator performance for various situations. In particular, it's important to examine situations in which the estimator system has not been trained, to determine reliability of estimator performance in situations that differ from those on which the estimator was trained.

Future Work

- The Kalman Filter is a famous model-based state-estimator algorithm providing optimized iterative estimates of the unknown disturbance reducing sensor and process noise as anticipated.

Simulation Results

- An optimization of state-estimator design, the known optimal Kalman estimator is an optimal iterative system
- The mean square error is:
\[ E\{e(t)^2\} = E\{y(t)^2\} - E\{u(t)^2\} \]

Obtaining Sensor State-Observability

- Obtaining sensor state-observability is an important property of the estimator, in that we need to see if the state vector can be accurately estimated from the available measurements.

Unknown Input Estimator Design

- The Kalman Filter is a famous model-based state-estimator algorithm providing optimized iterative estimates of the unknown disturbance reducing sensor and process noise.

With an unknown input estimator the input to the system, in this context the beam current, is modeled as a disturbance $d(t)$:
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