Real-time diagnostic data fusion using the RAPTOR transport code in combination with an Extended Kalman Filter with application to diagnostic fault detection and disruption prediction.

Federico Felici
Eindhoven University of Technology (The Netherlands)
Department of Mechanical Engineering
Control Systems Technology Group

With many collaborators: C.J. Rapson, W. Treutterer, M. Reich C. Piron, O. Sauter, H. van den Brand, T. Blanken, …
Real-time data fusion using diagnostics + models

- Objective: merge data from multiple diagnostics into a single, consistent estimate of the plasma state in real-time.
Real-time data fusion using diagnostics + models

• Objective: merge data from multiple diagnostics into a single, consistent estimate of the plasma state in real-time.

• Applications:
  • feedback control
  • discharge supervision/monitoring and forecasting...
  • fault detection
Real-time data fusion using diagnostics + models

- **Objective:** merge data from multiple diagnostics into a single, consistent estimate of the plasma state in real-time.
- **Applications:**
  - feedback control
  - discharge supervision/monitoring and forecasting
  - fault detection
- **Make use of a model-based, dynamic state observer**
  - eg Kalman Filter, Particle Filter, Luenberger observer, Recursive Bayesian estimator, ...
  - We will use the Extended Kalman Filter
Real-time data fusion using diagnostics + models

• Objective: merge data from multiple diagnostics into a single, consistent estimate of the plasma state in real-time.

• Applications:
  • feedback control
  • discharge supervision/monitoring and forecasting
  • fault detection

• Make use of a model-based, dynamic state observer
  • eg Kalman Filter, Particle Filter, Luenberger observer, Recursive Bayesian estimator, …
  • We will use the Extended Kalman Filter

• What do we mean by ‘state’?
  • Here we mean state as represented in a physics-based dynamic plasma evolution model.
Control of complex interconnected systems: Centralized state reconstruction & supervision

- Actuator commands to Tokamak
- Measurements from Tokamak

[Real-time control]

Supervision

- Density Controller
- Beta Controller
- q profile controller

Controllers

- MHD controller
- Shape controller

Observer

- Plasma State Reconstruction
- interferom.
- ECE
- magnetics
- MSE
- ...
Traditional practice of plasma control - direct link between diagnostics, controllers and actuators
Static fits vs. dynamic state observer

• ‘Static’ solutions (also offline)
  • ‘inversion’: measurements $y = h(x) \rightarrow x = h^{-1}(y)$ or ‘fit’ $\min_x \|y - h(x)\|$
    - e.g. Grad-Shafranov equilibrium reconstruction, spline fitting, abel inversion
  • Regularization often needed.
  • Diagnostic quality/availability limits reconstruction accuracy.
  • Every time step treated independently, no time history, no model.

• Dynamic state observers: solution for sensor fusion problem
  • Include model the system time-evolution in the estimation.
  • Capabilities:
    - Multirate, non-synchronous
    - Varying accuracy and availability..
  • Many examples in engineering systems
    - Smartphones, cars, …
• Assume model of the system w. additive noise
  • $x_{k+1} = f(x_k, u_k) + w_k$
  • $y_k = h(x_k) + v_k$
  - state: $x_k$, input: $u_k$, output: $y_k$
  - process noise: $w_k$, sensor noise: $v_k$ with covariance matrices $Q_k$, $R_k$
Dynamic state observer and the Kalman Filter

• Assume model of the system w. additive noise
  • $x_{k+1} = f(x_k, u_k) + w_k$
  • $y_k = h(x_k) + v_k$
    - state: $x_k$, input: $u_k$, output: $y_k$,
    - process noise: $w_k$, sensor noise: $v_k$ with covariance matrices $Q_k$, $R_k$

• Dynamic state observer
  • Start from previous state estimate $x_{k-1|k-1}$
  • Predict state at next time using dynamic model $f( )$
    $x_{k|k-1} = f(x_{k-1|k-1}, u_k)$
  • Predict output at next time using synthetic diagnostic $h( )$
    $\hat{y}_k = h(x_{k|k-1})$
  • Update state using measurement residual
    $x_{k|k} = x_{k|k-1} + L(y_k - \hat{y}_k)$
Dynamic state observer and the Kalman Filter

• Assume model of the system w. additive noise
  • $x_{k+1} = f(x_k, u_k) + w_k$
  • $y_k = h(x_k) + v_k$
    - state: $x_k$, input: $u_k$, output: $y_k$
    - process noise: $w_k$, sensor noise: $v_k$ with covariance matrices $Q_k, R_k$

• Dynamic state observer
  • Start from previous state estimate $x_{k-1|k-1}$
  • Predict state at next time using dynamic model $f(\ )$
    $x_{k|k-1} = f(x_{k-1|k-1}, u_k)$
  • Predict output at next time using synthetic diagnostic $h(\ )$
    $\hat{y}_k = h(x_{k|k-1})$
  • Update state using measurement residual
    $x_{k|k} = x_{k|k-1} + L(y_k - \hat{y}_k)$

• Kalman filter: if the system is linear: $x_{k+1} = Ax_k + Bu_k + w_k$, $y_k = Cx_k + v_k$
  • L matrix: solution of an algebraic matrix (Riccati) equation.
  • Optimal linear estimator for linear systems with gaussian noise.
Observers for nonlinear systems: the Extended Kalman Filter

• Nonlinear model

\[ x_{k+1} = f(x_k, u_k) \]
\[ y_k = h(x_k) \]
Observers for nonlinear systems: the Extended Kalman Filter

- Nonlinear model

\[
\begin{align*}
x_{k+1} &= f(x_k, u_k) \\
y_k &= h(x_k)
\end{align*}
\]

- Extended Kalman Filter (EKF).
  - Recursive Bayesian filter for Gaussian multivariate distributions.
  - Difficult to make rigorous statements of optimality but it ‘works’.

\[
\begin{align*}
\hat{x}_{k|k} &= \hat{x}_{k|k-1} + L_k[y_k - h(\hat{x}_{k|k-1})] \quad \text{state meas. update} \\
\hat{x}_{k+1|k} &= f_k(\hat{x}_{k|k}, u_k) \quad \text{Predicted state} \\
L_k &= S_{k|k-1}H_k^T\Omega_k^{-1}, \Omega_k = H_kS_{k|k-1}H_k^T + R_k \quad \text{Kalman gain} \\
S_{k|k} &= (I - S_{k|k-1}H_k^T\Omega_k^{-1}H_k)S_{k|k-1} \quad \text{covariance meas. update} \\
S_{k+1|k} &= F_kS_{k|k}F_k^T + G_kQ_kG_k^T \quad \text{covariance time update}
\end{align*}
\]

- Two matrices to be tuned:
  - \(Q_k\): State disturbance covariance: degree of trust in model
  - \(R_k\): Sensor noise covariance: degree of trust in measurements

Need Jacobians
What about systematic (e.g. modeling) errors?
Parameter adaptation vs. disturbance estimation

- Parameter adaptation (not recommended):
  - Use measurement to estimate uncertain model parameters
    - e.g. [Xu, IEEE trans. plas. sci 2010], [Santiago et al, ICSTCC, 2011]
  - Update model in real-time?
  - Disadvantages:
    - nonlinear problem, time-varying model..
What about systematic (e.g. modeling) errors?
Parameter adaptation vs. disturbance estimation

- **Parameter adaptation (not recommended):**
  - Use measurement to estimate uncertain model parameters
    - e.g. [Xu, IEEE trans. plas. sci 2010], [Santiago et al, ICSTCC, 2011]
  - Update model in real-time?
  - Disadvantages:
    - nonlinear problem, time-varying model..

- **Disturbance estimation (preferred):**
  - Assume unknown additive (constant) disturbance on state equation
    - $x_{k+1} = f(x_k, u_k) + d_k + w_k$ (model state equation - plasma physics model)
    - $d_{k+1} = d_k + w^d_k$ (disturbance state equation - random walk assumption)
    - $y_k = h(x_k) + v_k$ (output equation - synthetic diagnostic)
  - Augment state: $z_k = [x_k ; d_k]$
    - Estimate both using Kalman Filter
  - Modelling errors will be ‘absorbed’ into the time-varying $d_k$ estimate.
Dynamic observer for tokamak state estimation: merge RT diagnostics with model predictions

- **Controller**
- **Observer**
- **Diagnostic model**

Model-based, dynamic state estimator ("observer")
Dynamic observer for tokamak state estimation: merge RT diagnostics with model predictions

- Generic solution: ‘full tokamak’ simulation, merge all diagnostics
- First step: profile reconstruction. Simulation step using RAPTOR

Model-based, dynamic state estimator ("observer")
What is RAPTOR?

- At its heart, RAPTOR is a 1D tokamak transport solver
  - RAPTOR = RApid Plasma Transport simulatOR
  - Solves 1D evolution of $\psi(\rho,t) + T_e(\rho,t)$, assumptions on $n_e$, $n_i$, $T_i$
  - [F. Felici NF 2011 and PPCF 2012]

- With some very special features
  - Very fast: up to 0.1ms per time step, ~5 steps per confinement time.
    - 300s ITER in <0.5s with dedicated hardware and compilation settings.
  - Real-time-control oriented
    - Returns linearizations around trajectory used for controller design.
    - Simple interface with controllers in matlab/simulink
  - Physics-based: contains relevant nonlinear effects in transport PDEs
    - Neoclassical BS and conductivity
    - Ad hoc analytical models for thermal transport
    - MHD effects: sawtooth reconnection and NTMs
RAPTOR-based state observer for profiles: Implementation on AUG (2014)

- **Ip**: Used to start/stop observer, and as constraint for $\psi$ eq.
- **ECE**: Measurement to correct model-based $T_e$ estimate
- **DCR**: $n_e$ profile used directly for e.g. $j_{bs}$, $W_{th}$
- **TBM, NB/EC powers**: Actuator powers fed to real-time simulation
- **GS solver, $B_{tor}$**: Equilibrium information, $<1/R^2>$
- **No q profile diagnostics**: rely entirely on model

[ASDEX-Upgrade]

[F. Felici EPS 2014]
KF parameter choice

• How to choose sensor noise $R_k$?
  • $\sim \sigma^2$ of each diagnostic signal.
  • Artificially increase $\sigma^2$ for corrupt signals

• How to choose process noise $Q_k$?
  • parameterized by 3 parameters per profile:
    - faith in model at plasma center
    - faith in model at plasma edge
    - promote spatial correlation of profile

• Choice for AUG:
  • Good measurement for $T_e$, but inaccurate model (uncertain $\chi_e$), large $Q_k$
  • No measurements for $q$, but good model: trust model entirely, small $Q_k$
AUG RT diagnostic confidence and production states varies in time.
Real-time handling of diagnostic faults

• RAPTOR state observer is at the top of the food chain
  • Consumes ~150 RT signals.
  • Single corrupt signal, if undetected, might corrupt entire state estimate.

• Two-level protection strategy
  • 1) Rely on DCS signal confidence state flags provided by diagnostics.
    – (GOOD, CORRECTED, CORRUPT, RAW, INVALID)
  • 2) Check whether signals are reasonable w.r.t. model prediction.

• If a signal is bad:
  • Assign large uncertainty to measurement, so it is weakly trusted in state update. OR:
  • Hold previous trusted value OR:
  • Revert to a pre-calculated internal value.

• State estimation is robust against single diagnostic faults
  • Reverts to purely physics-model-based estimate in the worst case.
AUG RAPTOR State Observer - Present status

- Runs routinely every 10ms in stable version since July 2014
  - 11 spatial points $(\rho_{\text{tor},N})$
  - Includes internal model for NBHCD, ECHCD, radiation, …
AUG RAPTOR State Observer - Present status

• Runs routinely every 10ms in stable version since july 2014
  • 11 spatial points ($\rho_{\text{tor,N}}$)
  • Includes internal model for NBHCD, ECHCD, radiation, …

• Quality of the results
  • $T_e$ reconstruction is very good when ECE signals are good.
    - Uses ECE when available, else reverts to empirically tuned transport model
  • $q$ profile is good, some uncertainty if significant fraction of non-inductive current drive.
    - Uncertainties in RT CD modeling.
    - Lack of RT measurements of $q$ profile.
    - One-way coupling GS equilibrium $\rightarrow$ RAPTOR, not self-consistent yet.
      - 2-way coupling is in progress
      - Fast-ion pressure profiles planned

• Wishlist:
  • More RT diagnostics ($T_i$?)
  • better ECE forward model
  • better NBCD, ECCD models
Diagnostic fault detection by measurement residual analysis

- Example shown here for density profile observer
  - Developed separately by T. Blanken [MSc thesis TU/e 2014, EPS 2015]
- PDE model of particle diffusion + vacuum and wall inventory
- Validated against TCV data
- Residuals: difference between predicted and measured FIR signals on 14 chords
  - Fringe jump appears as a clear change in the residual.
  - Correct and/or change meas. covariance.
- ECE channels in AUG handled similarly.
Unexpected plasma behaviour detected by state disturbance analysis

‘Normal’ shot - AUG#30975

F. Felici - IAEA TM on fusion data P,V&A, Nice (FR) 1-3 June 2015
Unexpected plasma behaviour detected by state disturbance analysis

Shot with impurities and other problems (AUG 30920)
Outlook to model-based plasma supervision

- Supervising algorithm constantly verifies that plasma conforms to the expectation by monitoring the measurement residuals.
Outlook to model-based plasma supervision

• Unexpected events are accounted for in the reconstruction
Outlook to model-based plasma supervision

- Unexpected events are accounted for in the reconstruction
Example of supervised plasma termination for disruption avoidance.

- PCS intelligence - Level 2 disruption avoidance
  - [P. de Vries, this conference]
- ‘Plasma supervisor’ signals unexpected plasma behaviour, plasma is projected to leave ‘trusted’ zone.
- ‘Trusted’ ramp-down scenario is initiated, monitoring continues.
Outlook to model-based plasma supervision

• Build innovation/disturbance signal classifier using physics knowledge.
  • Classify events and report to plasma ‘supervisor’ (or offline report).
  • Test application for disruption avoidance by early soft-stop.
• Planned for MST1 experiments 2015-2016: TCV and AUG.
• Simulations to prepare for use in ITER.
• Longer term:
  • Implement similar system for magnetic control.
Conclusion

- RAPTOR-Observer installed in ASDEX-Upgrade (2014)
  - Parameter tuning is intuitive.
  - Handling time-varying signal quality/availability is key.
  - Good first results, good $T_e$ and reasonable $q$, plus many others.
- Analysis of innovations and state disturbance estimates
  - Gives information on plasma/diagnostic mis-behaviour.
- Outlook to RT classification of unexpected plasma behaviour
  - Offline analysis: detect interesting times in shot.
  - Plasma supervision and disruption avoidance.
Questions..