

Ahmad Alsaab System Modelling Engineer - ESI UK Ltd PhD in Mobile Robotics – Newcastle University Living in Wolverhampton - UK



www.esi-group.com

Parameter Estimation Methods for Fault Diagnosis using Modelica and FMI

Ahmad Alsaab, Morgan Cameron, Colin Hough and Purna Musunuru



Outline

- Introduction
- Local Estimator
- Global Estimator
- Conclusions



Introduction

- Methods used for condition estimation of a physical asset into three broad categories:
 - 1. Methods use only data. (black-box)
 - 2. Methods utilize a physical model of the system. (white-box)
 - 3. Both previous methods. (grey-box)



 We present two different parameter estimation methods using Modelica and FMI namely *local* and *global* estimators.



• The local estimator is implemented using Modelica and used to estimate parameters of one component inside the model.



The model with the Estimator

- The local estimator in this paper has been implemented in three different methods:
- 1) Direct Method 2) Recursive Least Squares 3) Particle Filter



• The local estimators are used to estimate the change in the mass M1 which changed from 5kg to 2kg at t=5s. The displacement of the M2 is used as an input of the estimator to tune the value of the mass M1.





Displacement of M2



Local Estimator Direct Method

• Modify model to replace target parameters by unknowns.

parameter Real M1;Real M1;Real x2;Input Real x2;Target parametersReplaced byState variablesReplaced by(sensor) inputs

- There needs to be a connected reference signal per parameter to be estimated.
- This estimator is:
 - 1. Very easy to implement.
 - 2. Very sensitive to noise in these signals.



Mass of M1 as a function of time

Recursive Least Squares Estimation

• The recursive least squares method (RLS) is used on-line and off-line to estimate parameters of static and dynamic linear systems

 $y = X^{T}A = a_{1}x_{1} + a_{2}x_{2} \dots + a_{n}x_{n}$ $K_{j} = P_{j-1}X_{j}(1 + X_{j}^{T}P_{j-1}X_{j})^{-1}$ $P_{j} = P_{j-1} - K_{j}X_{j}^{T}P_{j-1}$ $\hat{A}_{j} = \hat{A}_{j-1} - K_{j}(X_{k}\hat{A}_{j-1} - y_{j})$

Where j the current sample time, K is the estimator gain, P is the covariance matrix, \hat{A} is the parameters of the system

- This method is:
 - 1. Easy to implement.
 - 2. Robust against sensor noise.
 - 3. Only applicable to linear systems.





Mass of M1 as a function of time

Particle Filter

• Unlike the recursive least squares estimator, this algorithm is suitable for estimating the parameters of both linear and nonlinear systems.



Particle Filter Method



Mass of M1 as a function of time

• CPU-intensive in the case of large models.

Global Estimator

• The global estimator is implemented outside Modelica and uses the whole system model to estimate target parameters.





Global Estimator

Particle Filter

get it

- An example of using the state estimator for a thermal model of a wind turbine component.
- It can been seen from the output of the estimator that the friction in the system changed from 0.70 to 0.93.



- Our method is appropriate for multiple sensors and multiple faults.
- Example: model of a hydraulic system with two fault components and two pressure sensors and one displacement sensor.
- The amount of faults or leakages were controlled by a parameter inside the faulty components called *intensity*.



• An experiment was performed to simulate the faulty system, with fault intensities 0.2 for both fault components.





• The particle filter algorithm tuned the fault parameters to minimize the error between the data from the sensors and simulation





• Using sensors enabled the state estimator to estimate both faults.





Conclusions

- We examined the applicability of two different types of estimation methodology (local and global).
- Different parameter estimation algorithms using Modelica and FMI have been considered.
- Systematic representation of fault using SRA library *.
- We demonstrated how these methods can be applied to use external stimuli, in this case thermal sensor data, to obtain an estimate of the health of a real system.



* A. Kolesnikov et al Systematic Simulation of Fault Behavior by Analysis of Vehicle Dynamics, Proceedings of the 13th International Modelica Conference 2019, doi: 10.3384/ecp19157451





Copyright © ESI Group, 2020. All rights reserved.

17