DTU

FILTER

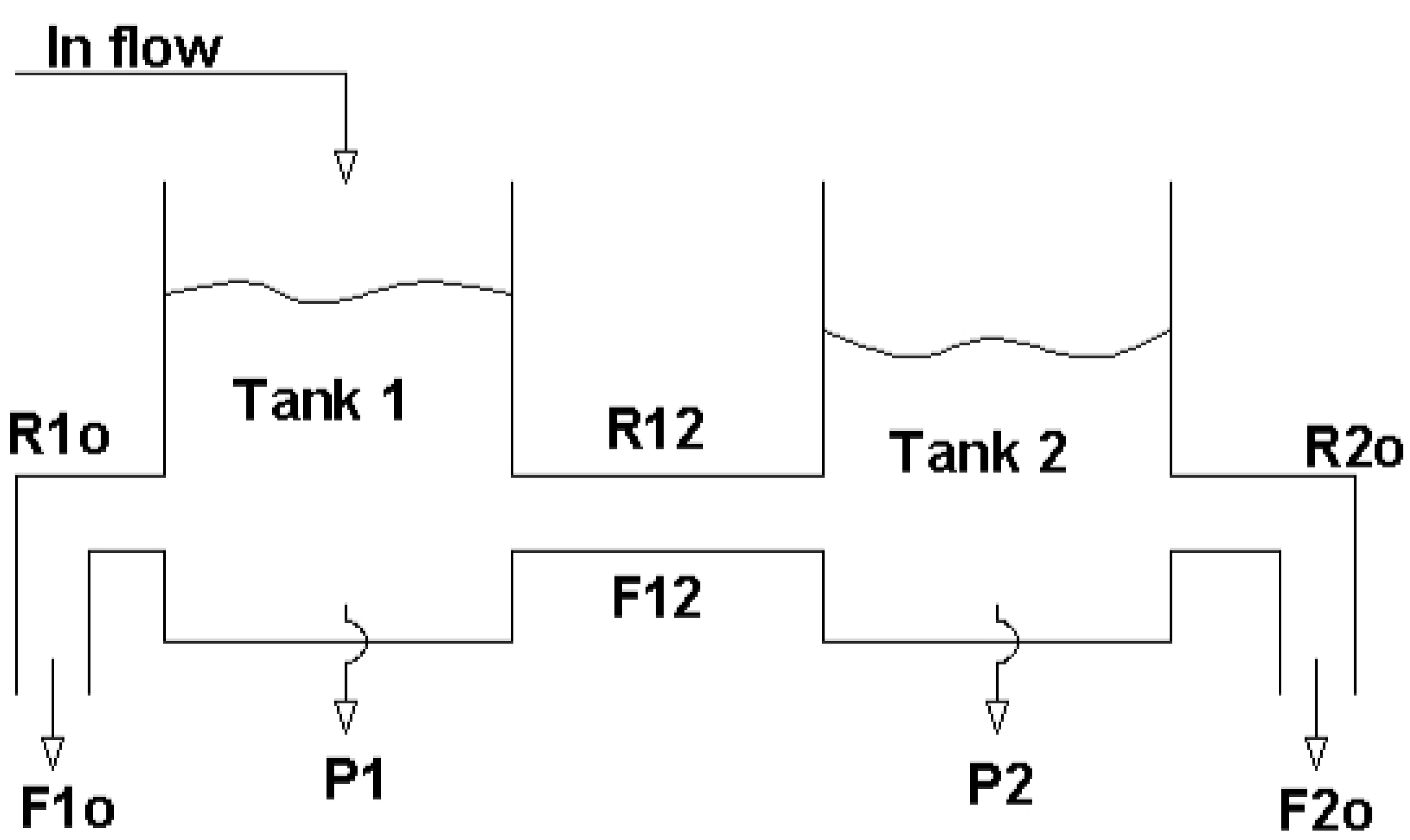
Inference in a complex, hybrid Dynamic Bayesian Network (DBN) is demonstrated using Particle Filtering (PF), Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF) and hybrid models in a non-strict Rao-Blackwellisation (RB) framework. We show that the UKF algorithms are superior and that their performance does not depend as heavily on the choice of network structure as opposed to the other algorithms.

Introduction

We model the fault detection system shown in Figure 1 using the 2-Time Slice DBN shown in Figure 2. The model relates continuous flow, pressure and resistance variables changing over time and includes noisy non-linear relations. Furthermore, we apply discrete measurement failures and resistance failures (pipe bursts and drifts).

Our objective is to infer the hidden variables based on noisy measurements of the flow. The network has 18,432 discrete states and is far too complicated for exact inference. Sub-optimally, we would like to use RB, i.e. sample all discrete variables and apply exact inference on the continuous nodes. As the dynamics are non-linear we apply approximate inference techniques (EKF/UKF) and call it 'non-strict' RB. To compare, we also apply a generic PF and hybrid models to infer the continuous nodes.

Showing how to do inference in such a general models is very important as it covers the modeling of many real-life problems.



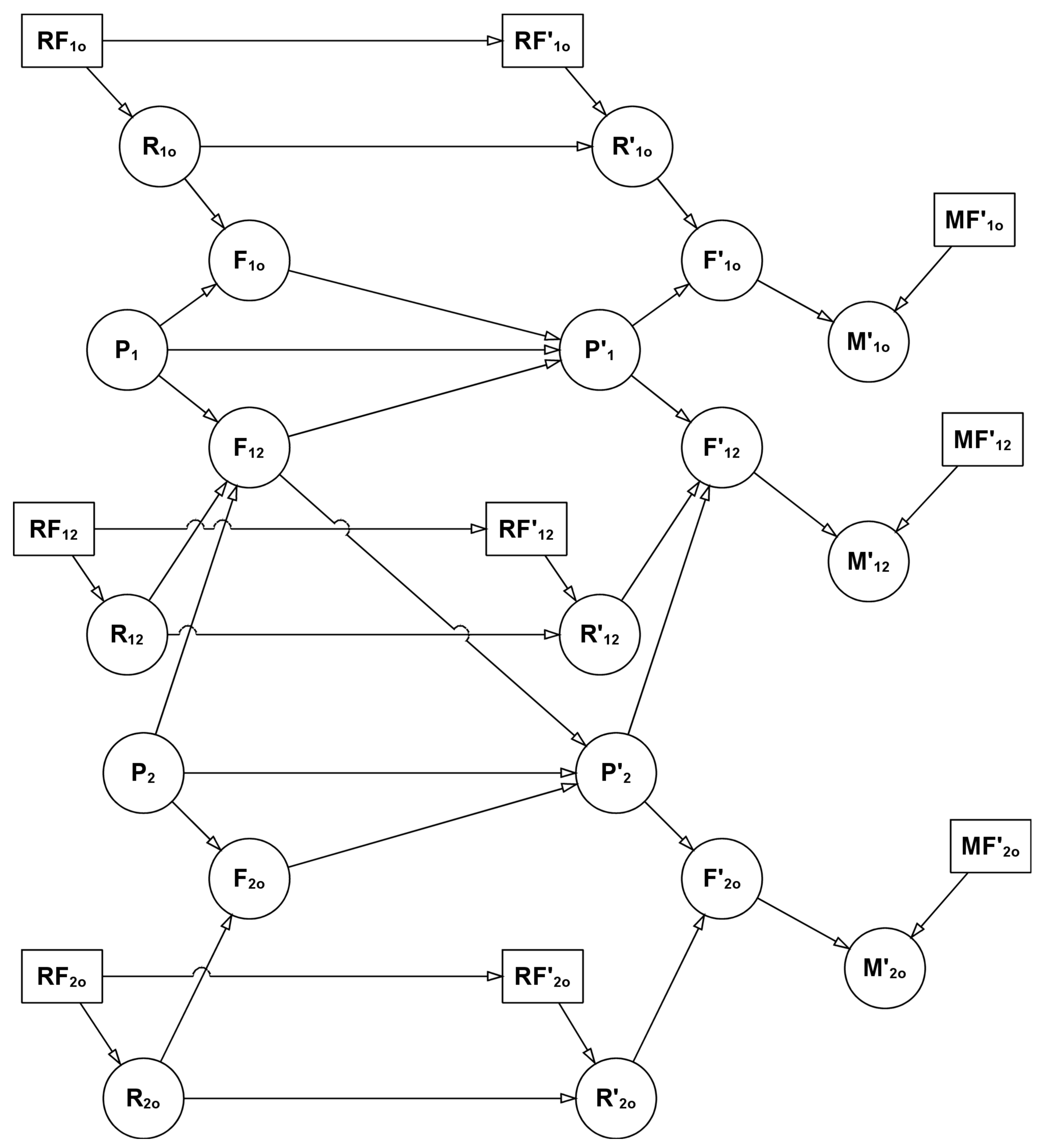


Figure 1+2. Watertank system and the 2T-DBN.

Methods

The evolution of the system is modelled by a *state transition or state process* model

$$p(\mathbf{x}_t|\mathbf{x}_{t-1}) \tag{1}$$

and *a state measurement* model

$$p(\mathbf{y}_t|\mathbf{x}_t) \tag{2}$$

and the noise on the measurements. $\mathbf{x}_t \in \Re^{n_x}$ are the states (hidden variables) of the system at time t and $\mathbf{y}_t \in \Re^{n_y}$ are the observations. For example, non-linear, non-Gaussian models can be expressed as

$$\mathbf{x}_t = \mathbf{f}(\mathbf{x}_{t-1}, \mathbf{v}_{t-1}) \qquad \text{and} \qquad \mathbf{y}_t = \mathbf{h}(\mathbf{x}_t, \mathbf{n}_t) \tag{3}$$

where $\mathbf{v}_t \in \Re^{n_v}$ is the process noise and $\mathbf{n}_t \in \Re^{n_n}$ is the measurement noise.