ABSTRACT

State estimation is largely applied to many engineering problems for estimating the states of a system using a sequence of noisy measurements. The knowledge of such states can be used for monitoring, fault diagnosis and for enhancing the control performance. Many Bayesian state estimation methods have been developed so far for providing solution to the nonlinear state estimation problem. Recursive implementations of Monte Carlo based statistical signal processing are known as particle filters which are potentially suited for estimating the states of highly nonlinear and non-Gaussian system. The Particle Filter (PF) requires the design of proposal density and the suitable choice of proposal distribution is the key design issue as it can significantly affect the performance of the filter. The primary objective of this research work is to investigate on the estimation performance of the particle filtering method with different proposal densities and develop a novel fault diagnosis approach based on a multi-model method for stochastic nonlinear systems. The system considered in this work for carrying out the simulation study is Continuous Stirred Tank Reactor (CSTR). The CSTR is a typical chemical reactor system with complex nonlinear dynamic characteristics. It comprises of two state variables, the product concentration and reactor temperature. Simulations of the system and its state estimation have been carried out using MATLAB program in an open loop condition.

The Sequential Importance Resampling Particle Filter (SIR-PF) is designed and implemented for estimating the states of a stochastic nonlinear CSTR system. This filter uses a set of weighted particles to approximate the posterior distribution of the state vector and evolve the state estimates in parallel. It ensures that the particles of equal weight are formed through resampling. It assumes that the transition prior is the proposal density and the importance weights are obtained from the likelihood function. Simulation

studies were conducted under different realistic scenarios such as normal process operating conditions, initial state vector mismatch and process-model mismatch. It is shown that under normal operating conditions, as number of particles in the SIR-PF increases, the state estimates move closer to the true states but at the cost of high computational complexity. In practice, the number of particles is usually decided empirically by conducting some initial experiments. It is also shown that under conditions like initial state mismatch and process-model mismatch, the filter follows the trajectory of the true state of the process but with large estimation error. The coolant flow rate is chosen as the parameter of mismatch between the process and model because any change in that parameter affects both the product concentration and reactor temperature simultaneously. In addition, the Root Mean Square Error (RMSE) values are also calculated for all the above cases to assess the performance of this filter.

As the SIR-PF assumes transition prior as proposal density which does not account the current measurement to propose new particles, the SIR-PF may fail to closely track the trajectory of the true states. If the proposal density in the PF is designed by incorporating the most recent measurement or observation through a bank of nonlinear filters such as Kalman-based estimators, then the corresponding filter is referred as Local Linearization Particle Filter (LLPF). The Extended Kalman Filter (EKF) based on analytic local linearization is used to construct the suboptimal approximations for the proposal density in the PF. Hence, using EKF as a proposal for the PF leads to Extended Kalman Particle Filter (EKPF). The efficacy of this analytical local linearization particle filter is demonstrated through application to a nonlinear CSTR system and the results are compared with the SIR-PF. It must be noted that the usage of local linearization particle filtering algorithm significantly reduces the number of particles required for generating improved state estimates compared to the SIR-PF.

The EKF usually relies on a first order Taylor series approximation, but such approximations can sometimes lead to poor representations of highly nonlinear functions, thereby resulting in divergence of the filter. An alternative nonlinear Kalman-based filter is the Unscented Kalman Filter (UKF) where the above drawback has been overcome by using the concept of sample statistics. The UKF addresses the problem faced by the EKF by using a deterministic sampling technique known as the unscented transformation. The UKF provides better state estimates and also has the capability of generating heavier tailed distributions than the EKF. Hence, using EKF as proposal density for the PF may not always provide good estimates because of its limitations. If the EKF proposal is replaced by the UKF proposal, then the resulting PF can perform much better because the UKF is more accurate and also allows one to control the rate at which the tails of the proposal distribution go to zero. This method of filtering can also be called as statistical local linearization particle filter because the UKF performs statistical local linearization. The effectiveness of the Unscented Particle Filter (UPF) is tested through simulation on a CSTR system and the performance of the UPF is compared with that of EKPF. This work shows that utilizing the UKF in the particle filtering algorithm for generating an importance proposal can achieve improved state estimation than the EKPF. The divergence problem in the EKPF is also discussed.

Fault Detection and Isolation (FDI) is an increasingly important issue in designing systems with safety and reliability. Thus, this detection enables one to take appropriate corrective action before catastrophic failures. The model-based FDI methods are the most powerful fault diagnosis methods if the process is well modelled. The FDI approach based on a multi-model method is formulated in this work for stochastic nonlinear systems. The utmost challenge in developing the FDI approach for the nonlinear system is the presence of unmeasured (hidden) state variables. The above problem can be solved by the design of filters. A new UPF based Log-Likelihood Ratio

(LLR) approach for detection and isolation of faults in nonlinear stochastic systems is proposed. This UPF based FDI approach is designed to detect changes in the system behaviour and isolate a corresponding fault using a bank of UPFs running in parallel. The detection and isolation of faults are carried out through maximum likelihood estimation and hypothesis testing method. This new FDI approach assures that the estimated states move towards the higher likelihood region as the proposal density in the UPF is dependent on the most recent measurement. The effectiveness of the proposed method has been demonstrated through exhaustive simulation studies on a stochastic nonlinear CSTR system. This work specifically emphasizes on detection and isolation of component fault in the system and bias fault in the sensor. This approach is designed for the detection of abrupt faults and is unable to handle incipient faults. It requires sufficient knowledge of the possible system faults. It is shown that under the presence of modelling errors, the UPF based FDI approach provides higher degree of robustness than the generic PF based FDI approach.

The Van der Pol Oscillator (VPO) is the benchmark system for studying any dynamical systems with limit cycle oscillations due to its unique nature. It can exhibit both stable limit cycle and unstable limit cycle depending on the direction of time. As the deterministic sampling technique is used in the particle filtering framework, chances of error being introduced in the design of such filter for VPO can be very minimum. Simulation tests were carried out on the VPO system to assess the state estimation performance of UPF. The simulation findings suggest that the UPF is far superior to SIR-PF under normal conditions, initial state mismatch and large measurement noise. The UPF also proves to be more robust to the error induced in the state estimator model of VPO.