Estimation of unmeasured states and monitoring of changes in the statistical parameters of the residues/innovations, form an important approach towards model-based fault detection & diagnosis (FDD). This requires the formulation of system dynamics in the state-space framework, wherein the conditional probability density function (*pdf*) of the state-vector X_k, conditioned on the measurement z_k, is propagated through a predictor-corrector process to obtain the optimum estimate of the state, while minimizing its error covariance. The Bayesian formulation yields the conditional *pdf* of the k_{th} state, $p\{X_k|z_k\}$, which is equated to the likelihood function, $p\{z_k|X_k\}$ & the prior pdf $p\{X_k|z_{k-1}\}$ and it is this formulation which governs the Bayesian estimation methodology. Here an overview of the Bayesian estimation problem is presented, which discusses the formulation of the Kalman filter as a Bayesian estimator resulting in a closed form solution, provided the dynamics are linear and the uncertainties are Gaussian. The *sequential Monte-Carlo filters* (SMC), or *particle filters*, which addresses both non-linear & non-Gaussian problems, but do not offer a closed form solution, are also introduced. The unscented Kalman filter *(UKF),* which overcomes some of the disadvantages of the particle filter in terms of being computationally intensive & not guaranteeing convergence for all initial sample sets, are also introduced. The model-based diagnostic problem, by study of the behavior of the estimated states, X_k & the residues [$r_k = (Z_k - HX_k)$], along with the convergence of the error covariance matrix P_k, and by use of multiple-model filtering, GLR (generalized likelihood ratio) methods, sequential probability ratio tests (SPRT) on the residues, etc. are also explained, along with typical applications in process & electrical equipment.