Online measurements of key process variables are restricted by inadequacy of measurement techniques or low reliability of measuring devices. Even if appropriate instrumentation exists, the key performance indicators are normally determined by offline sample analysis in laboratory or online product quality analyzers, which are often expensive and require frequent and high-cost maintenance. Furthermore, discontinuity and significant delays associated with laboratory analysis or slowly-processed quality measurements of online analyzers can reduce the efficiency of control policies. In industrial processing plants, such limitations can have a severe influence on the quality of products, production of waste, and safety of operations.

In the last two decades, there has been a growing interest in the development of *inferential models*, also called *soft sensors*, to provide frequent online estimates of quality variables on the basis of their correlation with readily-available process measurements. Such predictive models devoted to producing real-time estimates of desired plant variables can help to reduce the need for measuring devices, improve system reliability and develop tight control policies. There are several advantages of inferential sensors in comparison with traditional instrumentation:

1. They give more insight into process through capturing the information hidden in data.
2. They are emerging technology which allows industrial users to improve productivity, to become more energy efficient, to reduce environmental impact, and to improve business profitability by reducing the production cost associated with off-specification products.
3. They can easily be implemented on existing hardware and maintained when system parameters change.
4. They involve no capital cost.

The range of tasks fulfilled by inferential sensors is broad. At a very general level, these fields can be distinguished as follows:

1. **Online applications aimed at substituting and/or complimenting physical sensors* i.e.*
   - Predicting the key quality variables
   - Intelligent control
   - Monitoring and analysis of process trends

2. **Offline applications aimed at providing operation assistance tools* i.e.*
   - Diagnosis of process operations
   - Knowledge based engineering design
3. Heuristics and logic in planning and scheduling of process operations
4. Modeling languages, simulation and reasoning
5. Intelligence in scientific computing

Depending on the level of *a priori* knowledge of the process, three different classes of inferential models can be developed: knowledge-driven, data-driven and gray-box models. Knowledge-driven models, also called first-principles models, are developed on the basis of first principles analysis and, thus, require full phenomenological knowledge about the underlying mechanisms. Although first-principles models have many advantages, they can often be expensive and time-consuming due to the complexity of industrial processes. In contrast to this, data-driven models are constructed only based on the historical relations among the existing measurements, and prevents one from the laborious study of complicated chemical and physical phenomena involved. Data-driven models, also called black-box models, are thus proposed for situations in which physical understanding of the process under investigation is absent or not relevant. In between the two extremes, there are many combinations of knowledge-driven and data-driven models possible. The prior knowledge offered by the simplified first principles analysis forms the core of a so-called gray-box model, while data-driven methods can compensate fractions which cannot be modeled easily in terms of phenomenological models. Satisfactory results of gray-box techniques have been widely reported in literature, because any available source of information is exploited to refine the models.

An inferential sensor design procedure is an iterative process consisting of the following steps:

1. Process data analysis
   1.1 Selection of relevant variables
   1.2 Data pre-processing
2. Model identification
   2.1 Model structure selection
   2.2 Model parameter estimation
3. Model validation
   3.1 Offline performance evaluation
   3.2 Online performance verification

Development and implementation of inferential sensors entail many challenges that may arise due to the varying quality of industrial data. In the context of process industry, measurement noise, missing values, outlying observations, multi-rate data, measurement delay, and drifting data are the common factors affecting the quality of process data. The satisfactory performance of inferential sensors can be achieved only if such challenging issues are addressed. Despite the increasing number of publications dealing with industrial applications, yet several issues remain open for future investigation. Due to the demonstrated potential of Bayesian methods in dealing with certain outstanding issues associated with inferential modeling, interest in investigating these methods has grown enormously in recent years. As indicated by existing research efforts, Bayesian methods suggest a general solution for many types of systems including linear and nonlinear systems, in the presence of Gaussian or non-Gaussian disturbances, with or without constraints, and in dealing with regular or irregular data samples. Combined with a suite of inference and learning algorithms, Bayesian methods have proven to be powerful in many applications. However, these methods have not been widely applied to inferential modeling practices in the process industry.