Chapter 1
Advanced Process Monitoring

John D. Hedengren

Abstract Measurement technology is advancing in the oil and gas industry. Innovations such as wireless transmitters, reduced cost of measurement technology, and increased regulations that require active monitoring have the effect of increasing the number of available measurements. There is a clear opportunity to distill the recent flood of measurements into relevant and actionable information. Methods include a filtered bias update, Implicit Dynamic Feedback, Kalman Filtering, and Moving Horizon Estimation. The purpose of these techniques is to validate measurements and align imperfect mathematical models to the actual process. The objective of this approach is to determine a best estimate of the current state of the process and any potential disturbances. The opportunity is in earlier detection of disturbances, process equipment faults, and improved state estimates for optimization and control.

1.1 Introduction

Over the past 10 years many sectors of the oil and gas industry have seen a dramatic increase in the number and quality of available measurements. To capture the benefits of increased available measurements, the information must be distilled into relevant and actionable information. This chapter reviews the current state of the art of industrial practice in the downstream area with a discussion of potential opportunities to upstream.

One such opportunity is the increase in the available bandwidth to monitor upstream drill string dynamics. Recently, new technology has been deployed to drastically increase the data transmission rate to the Bottom Hole Assembly (BHA) or along the drill string. Mud pulsing was previously the most common form of communication where 3-45 bits per second could be transmitted from the BHA to the

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surface monitoring system via a series of pressure waves through the inner annular pipe. In addition to providing a communication pathway, the pumped mud removes tailings and cools the drill bit. As the depth of drilling increases, the attenuation of mud pulses increases and mud pulse data is frequently unavailable. Recently, wire-in-pipe technology, provided by NOV's IntelliServ, has increased this rate by approximately 10,000 times (see Figure 1.1) [20]. This increase in information allows

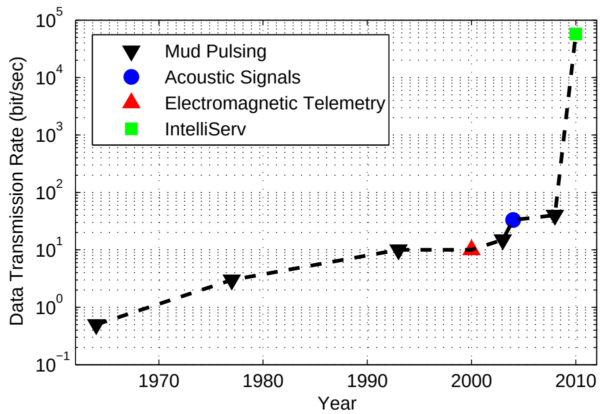

Fig. 1.1 Best available data transmission rates in upstream drill strings [15] [13]. The recent increase in throughput and bi-directional communication has created a new opportunity for better utilizing the information. Without interpretation, the increased data does not necessarily lead to increased understanding or value.

two-way communication and presents opportunities for improved monitoring and control of directional and under-balanced drilling. Similar improvements in measurement technologies are occurring in other parts of the oil and gas industry. This chapter is concerned with ways to better synthesize the data with process knowledge to capture the most benefit. These include a filtered bias update, Implicit Dynamic Feedback, Kalman Filtering, and Moving Horizon Estimation.

Moving Horizon Estimation (MHE) is an optimization approach that aligns process models with available measurements to determine a best estimate of the current state of the process and any potential disturbances. The opportunity is in earlier detection of disturbances, process equipment faults, and improved state estimates for process control. Explicit approaches commonly used in current practice, such as measured variable bias updating and Kalman filters, are compared to the full optimization approach. Formerly, the downside to optimization approaches was the increased computational load required to solve the problem and the difficulty to obtain optimal tuning. This chapter discusses techniques to overcome both of these obstacles to enable fast and reliable solutions that are tuned to optimally utilize measurement information in model predictive applications.

1.1.1 Time-Scales of Process Monitoring

Measurements of slow or fast processes pose unique challenges. For example the slow fouling of a heat exchanger [33] or the fast build-up of hydrates [10] are two examples of processes with different process time constants. With fouling or plugging as one of the top loss categories industry-wide, there are many opportunities for utilizing measurement technology to monitor the short or long term reliability [16]. In particular, deep-sea pipeline monitoring poses a challenge due to the remote environment, intermittent weather incidents, and gradual fatigue factors [4]. There is a desire for improved monitoring of existing and new projects to give insight into the conditions that lead to failure. Analytical models utilize the data to monitor the operational integrity for flow assurance and riser integrity.

1.1.1.1 Frequency of Optimization Updates

Before discussing techniques for measurements, it is informative to review the corresponding optimization applications. Optimization can occur after a model is synchronized to available process measurements or inputs. Process optimization is used in the oil and gas industry at various phases of the process lifecycle. As shown in Figure 1.2, optimization of process design occurs once at the beginning of the lifecycle. This may include sizing of vessels, valves, etc. Optimization is also used to guide flow of products with Supply Chain Optimization. This may occur on a weekly to monthly basis. Dynamic optimization is concerned with long time periods as well and covers processes such as defouling, turn-around operations, and production scheduling. On an hourly basis Real-Time Optimization (RTO) with large-scale steady state models is used to determine new targets for plant-wide operations [6] [17]. On the second to minute time-scales, Model Predictive Control (MPC) applications implement the steady-state targets.

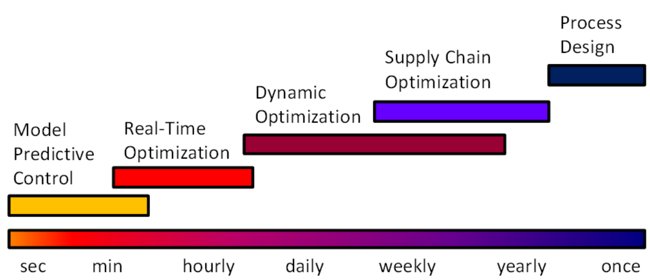

Fig. 1.2 Time-scales of optimization technologies applied in oil and gas industry.

1.1.1.2 Frequency of Model and Measurement Alignment

Just as optimization is applied at varying time-scales, measurement reconciliation is performed at varying time-scales as well that are analogous to the optimization approaches (see Figure 1.3). A sufficiently accurate model is required to optimize the

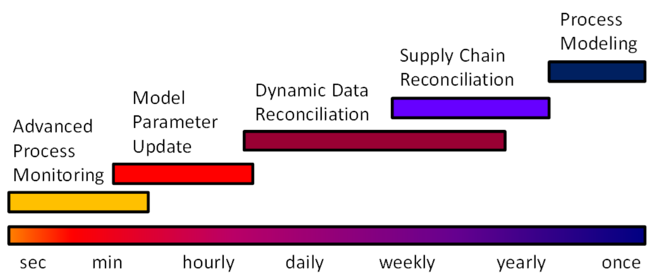

Fig. 1.3 Time-scales of measurement reconciliation applied in the oil and gas industry.

design of a process. During the lifecycle of a facility, this modeling activity is typically conducted during the design and start-up of a new process. Data from other related processes are typically used to generate an initial process model which is then refined after the process unit comes online. Supply chain reconciliation seeks to align a model to the available inventories, capacities, and constraints [18]. Dynamic data reconciliation is used for large-scale dynamic models over long time horizons [19] [21] [1]. It is used in conjunction with dynamic optimization to align the model parameters with dynamic data [31]. For RTO applications, a precursor step is to adjust fouling factors, tray efficiencies, and other parameters with a Model Parameter Update (MPU) [6]. This MPU may include single or multiple steady-state snapshots or the process measurements. One restriction is that the process must be at steady-state for the MPU. Finally, Moving Horizon Estimation (MHE) is a multivariable approach for optimal measurement reconciliation in a dynamic model [29]. MHE applications are typically performed on a time-scale faster than that of the process time constant of interest. It typically executes in the range of seconds to minutes and can be used to provide updates to MPC applications.

1.1.2 Overview of Chapter

This chapter is a review of strategies to incorporate measurements in optimization and monitoring applications. The mathematical models used in these applications have unmeasured or unmodeled disturbances that cause the model predictions to drift from actual values. This realignment of model and measurement can occur with a variety of techniques ranging from simplified to sophisticated. When the application provides information in real-time, the results must be returned within a specified cycle time. Details on efficient implement of the techniques are also presented in this chapter with a practical guide that includes example applications.

The focus of this chapter is on measurement reconciliation for fast time processes in the range of seconds to minutes. New and established techniques are discussed that improve the information extraction from the measurements to allow fundamental understanding of a process.

1.2 Numerical Solution with Dynamic Models

The approach taken in this chapter is simultaneous solution of the model equations and objective function. The general model form consists of nonlinear differential and algebraic equations (DAEs) in open equation format as shown in Equation 1.1.

$$\begin{aligned} 0 &= f\left(\frac{\partial x}{\partial t}, x, u, d\right) \\ 0 &= g(y, x, u, d) \\ 0 &\leq h(x, u, d) \end{aligned} \tag{1.1}$$

The optimization calculates future states in the horizon that are uniquely specified by the initial state x_0, a given sequence of inputs $u = (u_0, u_1, \ldots, u_{n-1})$, and a calculated set of disturbances $d = (d_0, d_1, \ldots, d_{n-1})$. In Figure 1.4, u and d are shown as discrete values over the horizon. Variables calculated from differential and algebraic equations are continuous over the time horizon. The solution of the open equation

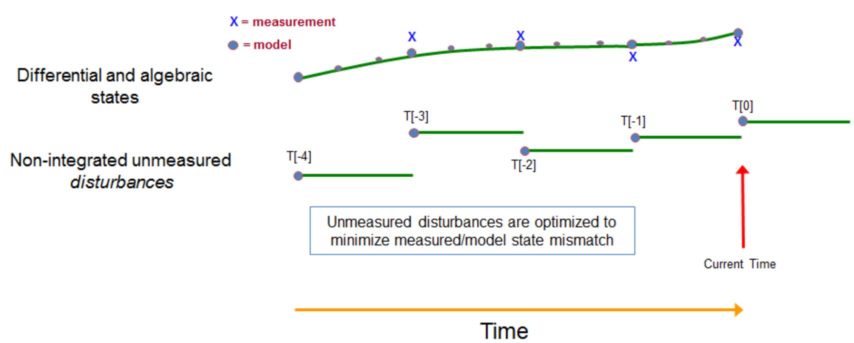

Fig. 1.4 Dynamic equations are discretized over a time horizon and solved simultaneously.

system is accomplished by converting the differential terms to algebraic equations with orthogonal collocation on finite elements [5] or also known as direct transcription [7]. Order reduction may assist in understanding the most important states that dominate the system dynamics [11], but in general the full system can be solved directly.

The solution of the estimation problem is solved with an implicit solution technique such as large-scale NLP solvers [19] [2]. Other methods include the direct shooting approaches [14] or the explicit solution [27] [12] for simplified problems. The difference between competing implicit solution techniques is how the state equations are satisfied. Direct single or multiple shooting solves the state equations to a convergence tolerance for every iteration. Using orthogonal collocation on finite elements, the state equations are only satisfied at a converged solution. This generally leads to a more efficient solution, especially for large-scale problems with many decision variables [9].

1.3 Review of Current Strategies

Advanced Process Control (APC) has produced significant benefits in many of the oil and gas sectors, including upstream, refining, and chemicals production [26]. However, simpler control applications such as PID controllers are often preferred in particular situations. Measurement reconciliation also ranges from simple to complex [32]. Simple techniques include filtered bias updates or Implicit Dynamic Feedback (IDF^{TM}). More complex strategies include Kalman filtering and Moving Horizon Estimation (MHE). Each of these techniques are discussed below.

1.3.1 Filtered Bias Update

A predominant approach for measurement feedback into many of the popular APC commercial packages continues to be a filtered bias update [26]. Adding an output constant or integrating disturbance introduces insignificant computational overhead and is easy to tune. In the case of a constant disturbance, an additive model bias b is updated at iteration n with a filter α as shown in Equation 1.2

$$b_n = \alpha\,(z_n - y_n) + (1-\alpha)\,b_{n-1}, \quad 0 \leq \alpha \leq 1 \tag{1.2}$$

In this case, the difference between the measured state z_n and the predicted model y_n is used to update the offset of a controlled variable initial condition. With a weak filter with α near 1, almost all of the measurement value is accepted for updating the model predicted value. Strong filters that accept less of the measured value may cause the corresponding APC application to respond slowly to unmodeled disturbances. The value of α is typically chosen to balance noise rejection with speed of reaction.

Advantages of Filtered Bias Update

1. Incorporated with many popular APC commercial packages
2. Single tuning parameter, α, that balances noise rejection with measurement tracking speed
3. Insignificant computational overhead

Disadvantages of Filtered Bias Update

1. No capability to estimate parameters or unmeasured disturbances
2. No consideration of multivariable effects
3. Offset is present for integrating disturbances
4. Physical constraints may be violated

In order for the bias to be updated, certain qualifications may also be set to detect bad measurements. These qualifications are commonly upper and lower validity limits as well as a rate of change validity limit. The validity limits are applied to either the raw measurement or the raw bias. If any of the validity limits are violated, the measurement is rejected and the bias value remains constant. Rate of change validity limits are frequently set too restrictively for upset conditions, necessitating the need for operator intervention or automatic application switching to manual control.

1.3.2 Implicit Dynamic Feedback

Implicit Dynamic Feedback (IDF^{TM}) estimates unmeasured disturbances related to the predictions of the measured state variables. IDF^{TM}pairs a single measurement with a single unmeasured disturbance variable. The analogy to control is the Single Input, Single Output (SISO) controllers such as the ubiquitous PID controller. In the case of IDF^{TM}the unmeasured disturbance variable is adjusted to align the model with a process measurement. IDF^{TM}consists of two equations that can be solved simultaneously with the control problem over a preceding horizon interval.

The IDF^{TM}equations are similar to a proportional integral (PI) controller. The IDF^{TM}input is the difference between the measured state z and model state y. This is similar to the PI controller with a setpoint $(SP = z)$ and process variable $(PV = y)$. The output is an unmeasured disturbance variable d of the model and is analogous to the PI controller as the manipulated variable. This disturbance variable is adjusted proportional to the current and integrated measurement error as shown in Equation 1.3a. However, Equation 1.3a is not implemented in practice because of the integral term. To overcome this, the integral term 'I' is differentiated and the IDF^{TM}equations are solved as two separate expressions (see Equation 1.3b).

$$d = K_c\,(z-y) + \frac{K_c}{\tau_I}\int_{t=0}^{T}(z-y)\,dt \tag{1.3a}$$

$$d = K_c\,(z-y) + \frac{K_c}{\tau_I}I, \quad \frac{\partial I}{\partial t} = (z-y) \tag{1.3b}$$

The tuning parameters for IDF^{TM}are K_c and τ_I, the same as a PI controller. Using a large value of τ_I and small K_c has the effect of heavily filtering the error term for feedback. In this case the algorithm will take longer to match the plant. Using these tuning parameters and knowing the quality and types of measurements enables trading off of *speed of tracking the process* versus *stability concerns*.

Advantages of IDF^{TM}

1. Only two differential equations are required to implement IDF^{TM}
2. Similar tuning to a PID controller
3. Two intuitive parameters trade-off speed versus stability

Disadvantages of IDF^{TM}

1. Restricted to one-to-one pairing of a measurement to an unmeasured disturbance
2. Potential wind-up of the integral term
3. One step estimation horizon gives parameter values that may not project into the future for predictive applications (e.g. MPC)
4. Physical constraints cannot be enforced

IDF^{TM}has been successfully used for many years to provide on-line estimation measurement biases, catalyst activities, kinetic parameter adjustment factors and heat transfer coefficients. However, IDF^{TM}is limited to a past horizon length of one, pairing of only one measurement to one disturbance, and the inability to handle constraints.

1.3.3 Kalman Filter

With a Kalman filter, sequential measurements are used to obtain the state of the system with a linear model. To obtain this model, Jacobian information from Equation 1.1 are rearranged into the discrete state space form (see Equation 1.4) where A, B, C are constant matrices, u is the manipulated variable vector, x is the state vector, y is the vector of model outputs. In this case, the subscript n refers to the time step at which the model is computed.

$$x_{n+1} = Ax_n + Bu_n \tag{1.4a}$$

$$y_n = Cx_n \tag{1.4b}$$

The horizon of measurements is combined mathematically to generate the system's state at the current time with the Kalman filter as shown in Equation 1.5. The Kalman filter is divided into 4 subsets of equations. In Equation 1.5a the states $\overline{x}$ and covariance $\overline{P}$ are predicted in the absence of new measurement information. In the next step (see Equation 1.5b), the predictions are compared to the measured values. The innovation $\tilde{\delta}$ and innovation covariance S are the comparison of the model predictions to the measured reality. The innovation covariance S and covariance prediction $\overline{P}$ are then used to calculate the Kalman gain K in Equation 1.5c. As a final step, the new state and covariance estimates are computed in Equation 1.5d. The Kalman gain relates the fraction of the innovation $\tilde{\delta}$ and state prediction $\overline{x}$ that are used to construct the new state estimate x_n. Similarly, the Kalman gain relates the predicted covariance prediction to the new covariance prediction. Note that the covariance update is independent of the measurement values z_n and the time evolution is only a function of constant matrices.

$$\begin{aligned} \overline{x} &= Ax_{n-1} + Bu_n \\ \overline{P} &= AP_{n-1}A^T + Q \end{aligned} \tag{1.5a}$$

$$\begin{aligned} \tilde{\delta} &= z_n - C\overline{x} \\ S &= C\overline{P}C^T + R \end{aligned} \tag{1.5b}$$

$$K = \overline{P}C^T S^{-1} \tag{1.5c}$$

$$\begin{aligned} x_n &= \overline{x} + K\tilde{\delta} \\ P_n &= (I - KC)\,\overline{P} \end{aligned} \tag{1.5d}$$

The Kalman filter is optimal for unconstrained, linear systems subject to known normally distributed state and measurement noise [8]. The Extended Kalman Filter (EKF) or Unscented Kalman Filter (UKF) are an attempt to extend these techniques to nonlinear systems.

Advantages of the Kalman Filter

1. Optimal estimator for linear systems without constraints
2. Solution approach is accomplished through matrix multiplications, not an iterative optimization solution that is not guaranteed to converge
3. Covariance estimate provides confidence interval for state estimate

Disadvantages of the Kalman Filter

1. Restricted to linearized model state updates

2. Physical constraints cannot be enforced
3. Can only estimate model states, not model parameters
4. Cannot utilize infrequent measurements or those with variable time delay

EKF is able to predict the nonlinear state evolution by re-linearizing the model at each time instant. Some effort has been made to incorporate constraints with EKF although the state augmentation strategy for parameter estimation is still a limitation [34]. Kalman based techniques suffer from a number of limitations. For nonlinear or constrained systems, optimization techniques such as MHE are better suited to providing an estimate of the true system state.

1.3.4 ℓ_2-Norm Moving Horizon Estimation

Moving Horizon Estimation (MHE) outperforms the Extended Kalman Filter (EKF) in the presence of constraints [8]. Recent advances in computational capability and methods have improved the application of MHE to large-scale industrial systems [28]. Just as APC has demonstrated significant benefits by considering multivariate relationships, MHE is better able to utilize measurements and deliver a more accurate description of the current state of the process and disturbances [30].

By using an optimization framework the model and measurement values are aligned and present detailed information about the system dynamics. This optimization framework uses a receding horizon of process measurements. MHE attempts to optimally estimate the true state of the dynamic system, given a real-time stream of measurements and a model of the physical process. Offset free estimation and control is achieved by adding as many disturbance variables as the number of measurements [22] [25] [24]. The MHE objective function is posed as a squared error minimization of ℓ_2-norm error to reconcile the model with measured values.

Advantages of ℓ_2-Norm MHE

1. Least squares is intuitive and simple to implement
2. Model constraints can be added to model to improve the estimation accuracy
3. Optimal tuning has been established [23]

Disadvantages of ℓ_2-Norm MHE

1. Poor rejection of outliers or infrequent bad values common with real data
2. Difficult to obtain good estimates of P_0, Q, and R
3. Dense tuning matrices impractical for large-scale systems

4. Iterative optimization solution that may fail to converge in the required cycle time

In a MHE form amenable to real-time solution, the unmeasured disturbance variables d are adjusted to match the continuous model to discrete measured values [28].

$$\begin{aligned} \min_{d} \Phi &= \left\| \tfrac{z-y}{y} \right\|_{Q_y}^2 + \left\| d - \hat{d} \right\|_{Q_d}^2 \\ \text{s.t.} \quad 0 &= f(\dot{x}, x, u, d) \\ 0 &= g(z, x, u, d) \\ 0 &\le h(x, u, d) \end{aligned} \tag{1.6}$$

in which Φ is the objective function value, z is a vector of measurements at all nodes in the horizon $(z_0,\ldots,z_n)^T$, y is a vector of model values at the sampling times $(y_0,\ldots,y_n)^T$, Q_y is the inverse of the measurement error covariance, f is a vector of model equation residuals, x represents the model states, u is the vector of model inputs, d is the vector of model parameters or unmeasured disturbances, $\hat{d}$ is the vector of prior unmeasured disturbances, Q_d is a matrix for the weight on changes of disturbance variables, g is an output function, and h is an inequality constraint function. A graphical representation of the MHE ℓ_2-norm reconciliation is shown in Figure 1.5. The objective for this measured value is a quadratic function with the minimum target between the previous model and measured values. The full

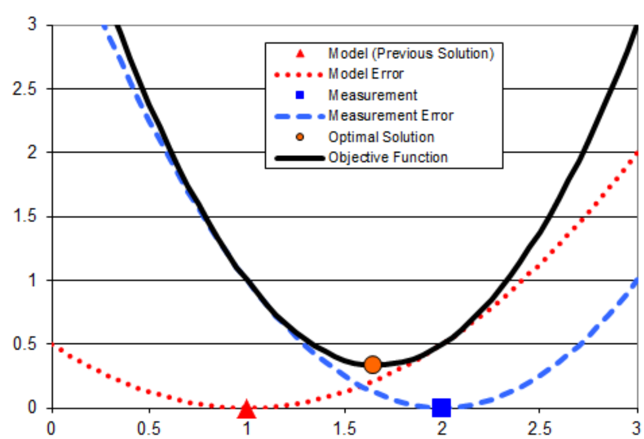

Fig. 1.5 Graphical representation of the ℓ_2-norm for a single measurement in the horizon.

estimation problem allows violation of the state constraints [30]. State equality constraints are relaxed and violations are penalized in the objective function. Without d the optimization problem found in Equation 1.6 does not allow state transition error because the state equations are exactly satisfied at a converged solution [3]. This can be overcome by creating a discontinuous state y and disturbance d with an additional equation $y = x + d$ for each state subject to state noise. This allows discontinuities in the y states while preserving the continuity of the x states. However, allowing state noise is undesirable when employing first principles models. For material and energy balances, allowing state noise reduces the predictive potential of the model. Instead, the only decision variables are selected as x_0 and d instead of $(x_0,\ldots,x_n,\ p)$ as in the full MHE problem. As the estimation horizon increases, the sensitivity of the solution at x_n to x_0 decreases. With a first-order approximation, the value of the final state x_n sensitivity decreases by $e^{-\frac{t}{\tau}}$ where τ is the approximate process time constant. For sufficiently long time horizons, it is then only d that has a significant effect on the current model state. Thus, it is generally unnecessary to estimate the initial states x_0 as degrees of freedom in the optimization problem.

1.3.5 ℓ_1-Norm Moving Horizon Estimation

A new form of MHE has been used in industry for a number of years that overcomes some of the limitations of the ℓ_2-norm MHE approach [9]. The objective function in Equation 1.7 is implemented in a form that is amenable to numerical solution of large-scale models. The use of an absolute value function is avoided by instead solving inequality constraints with slack variables. The slack variables and inequalities create an objective function that is smooth and continuously differentiable as a requirement for large-scale Nonlinear Programming (NLP) solvers.

$$
\begin{aligned}
\min_{d}\ & \Phi = w_m^T\left(e_U - e_L\right) + w_p^T\left(c_U + c_L\right) \\
\text{s.t.}\ & 0 = f(\dot{x}, x, u, p, d) \\
& 0 = g(y, x, u, d) \\
& 0 \le h(x, u, d) \\
& \\
& e_U \ge y - y_U \\
& e_L \ge y_L - y \\
& c_U \ge y - \hat{y} \\
& c_L \ge \hat{y} - y \\
& e_U, e_L, c_U, c_L \ge 0
\end{aligned}
\tag{1.7}
$$

in which Φ is the objective function value, z is a vector of measurements at all nodes in the horizon $(z_0,\ldots,z_n)^T$, y is a vector of model values at the sampling times $(y_0,\ldots,y_n)^T$, $\hat{y}$ is a vector of previous model values at the sampling times $(\hat{y}_0,\ldots,\hat{y}_n)^T$, w_m is a vector of weights on the model values outside a measurement dead-band, w_p is a vector of weights to penalize deviation from the prior solution, f is a vector of model equation residuals, x represents the model states, u is the vector of model inputs, d is the vector of model parameters or unmeasured disturbances, g is an output function, h is an inequality constraint function, e_U and e_L are slack variables to penalize model values above and below the measurement dead-band, and c_U and c_L are slack variables to penalize model value changes above and below the previous values. A graphical representation of the MHE ℓ_1-norm reconciliation is shown in Figure 1.6. Parameters are only adjusted if the measured value is more than the half of the dead-band away from the previous model value. Otherwise, the model is not adjusted because the measurement lies within the region of a flat objective function. In the case of Figure 1.6, the optimal solution lies at the edge of the measurement dead-band. This will always be the case for measurements that are more than half the dead-band distance from the prior model value. The MHE

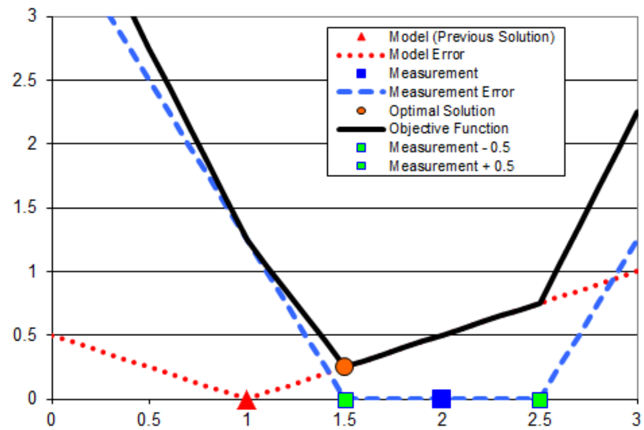

Fig. 1.6 Graphical representation of the MHE ℓ_1-norm for a single measurement in the horizon.

ℓ_1-norm objective has a number of advantages and challenges compared with other methods such as the Kalman filter or the MHE ℓ_2-norm. The next sections details the trade-offs between the different techniques.

1.3.5.1 MHE ℓ_1-Norm Advantages

An important MHE ℓ_1-norm advantage is less sensitivity to data outliers. This is important when dealing with industrial data where instruments drift or fail. Gross-error detection can eliminate a majority of bad data. With MHE ℓ_1-norm, any data that isn't filtered by gross-error detection has less impact on the parameter estimation and allows improved reliability of the solution. A squared error or ℓ_2-norm objective is more sensitive and will disproportionately weight values that are far from the model predictions.

An additional advantage of the MHE ℓ_1-norm is that only linear equations are added to the objective function. By not adding additional nonlinear expressions, the solution is generally easier for numerical solvers to find an optimal solution. In summary, the MHE ℓ_1-norm optimization problem with measurement noise dead-band has a number of advantages over the MHE ℓ_2 or squared error form of the objective function:

Advantages of MHE ℓ_1-Norm

1. Low sensitivity to data outliers
2. Linear objective function and sparse tuning techniques improve scaling to large-scale systems
3. Explicit measurement dead-band for improved noise rejection

Disadvantages of MHE ℓ_1-Norm

1. Additional equality and inequality constraints and variables
2. No optimal theory on best tuning parameters
3. Requires an iterative solver to reliably converge in a specified cycle time

1.3.5.2 MHE ℓ_1-Norm Challenges

The challenges with the MHE ℓ_1-norm optimization problem include increased complexity and size. Although the MHE ℓ_1-norm uses only linear expressions in formulating an objective function, there are additional slack variables and inequality expressions, which increases the size of the optimization problem.

Many of the MHE ℓ_1-norm challenges are due to the increased complexity in the solution techniques. Commercial and academic software has been developed to meet this challenge. The software used to generate the results in this paper is the APMonitor Modeling Language [**?**]. Filtered bias updating, Kalman filtering, IDF$^{\text{TM}}$, and MHE are implemented in this web-services platform through MATLAB or Python.

1.4 Example Application

As an example application, consider the problem of determining the flow of mud through the return annulus of a drilling pipe. In the return line, there is typically a flow paddle that rotates proportional to the flow rate. This flow paddle measurement is not very accurate so additional information such as pit tank level can be used to infer the return flow. Additionally, in Managed Pressure Drilling (MPD), a choke valve is adjusted to maintain well pressure [**?**] as shown in Figure 1.7. The flow,

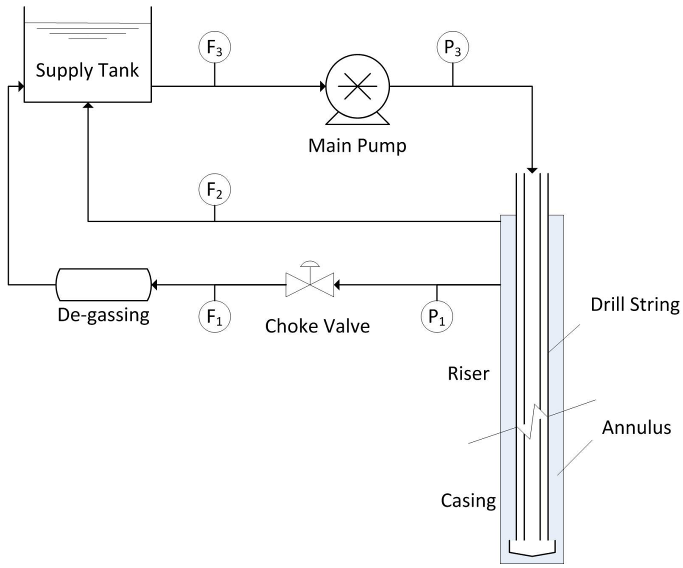

Fig. 1.7 Schematic of Managed Pressure Drilling.

pressure, and level measurements have noise, creating random fluctuations around the true values. The flow through the choke valve can also be estimated from the valve position and differential pressure across the valve (see Equation 1.8).

$$\tau \frac{\partial q}{\partial t} + q = C_v f(l) \sqrt{\left(\frac{\Delta P_v}{g_s}\right)} \tag{1.8}$$

For this example, the installed characteristic of the choke valve is assumed to be linear ($f(l) = l$) and the valve is fast acting ($\tau = 1sec$). Both the state and measurement noise are normally distributed with mean values of zero (see Figure 1.8). State noise has a standard deviation $\sigma_q = 0.1$ and measurement noise has a standard deviation $\sigma_r = 1.0$. The Kalman filter updates the state estimates by operating in two phases: predict and update. In the prediction phase, the calculated flow is modified according to the equation that relates flow q to the lift function $f(l)$ and the differential pressure, ΔP_v. For Kalman filters, the equation must first be linearized. With Extended Kalman filters, the nonlinear equations are re-linearized about the current state estimate. The other parameters including τ, C_v, and g_s are constants for a particular valve and fluid. For systems with multiple measurements, the covariance is used to tune the Kalman filter. In this case with one measurement, the variance is used instead. This information is essential for optimizing the update phase yet state

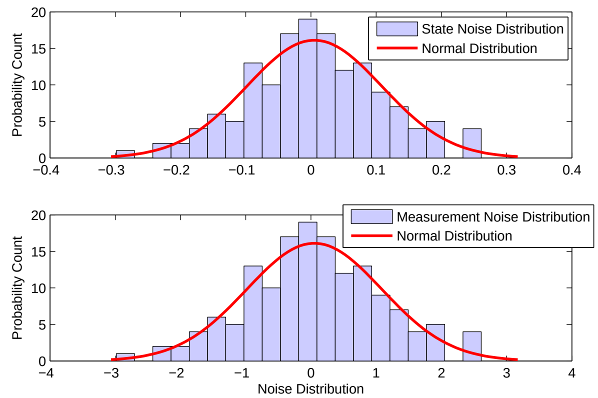

Fig. 1.8 Noise distributions of state and measurement noise. These distributions are used to optimally tune the estimators.

and measurement covariance information can be difficult to obtain. The results of the Kalman filter with the upper and lower 95% confidence intervals are shown in Figure 1.9. In the update phase, a measurement of the flow is taken from the trans-

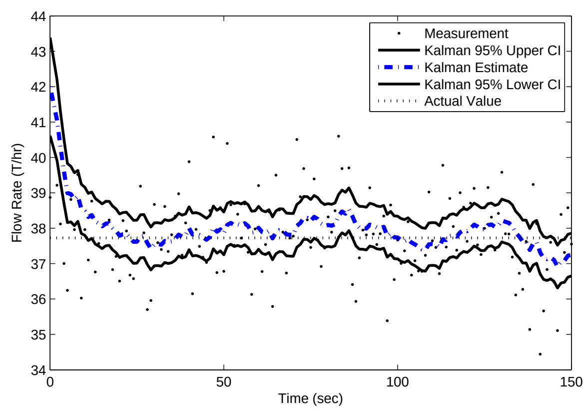

Fig. 1.9 The Kalman filter uses two phases, predict and update, to obtain an estimate of the true flow. During the predict phase, the model calculates an updated flow due to the latest reported model inputs. During the update phase, part of the flow measurement is used to update the state, inversely proportional to the variance of the measurement error.

mitter. Because of the noise, this measurement has a certain amount of uncertainty. The calculated variance from the predict phase determines how much the new measurement affects the updated prediction. If the model prediction drifts away from the real flow, the measurements from the flow transmitter should pull the flow estimate back towards the real flow but not disturb it to the point of introducing all of the noise from the measurement. This model update could also employ other measurements such as mud pump speed, choke pressure, or supply tank level to infer the flow rate across the valve. For this simple example, only the valve position and flow measurements are used to predict the flow with a linear, first-order correlation. Each of the five techniques discussed in this chapter are compared over the same data set as shown in Figure 1.10. The filtered bias update and IDF^{TM}have been tuned to give

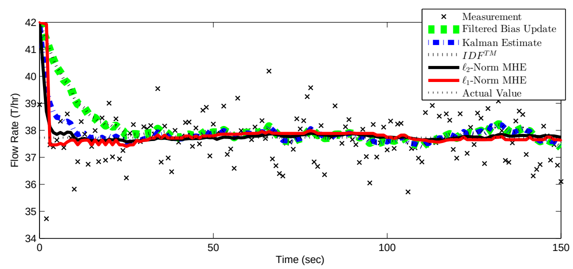

Fig. 1.10 Actual, measured, and estimated flows for filtered bias update, IDF^{TM}, the Kalman filter, ℓ_2-norm MHE, and ℓ_1-norm MHE.

equivalent responses. After an initialization period, they also align exactly with the Kalman filter results because the Kalman gain becomes constant after the estimate of P_n also converges to a constant value. The first four methods including filtered bias update, IDF^{TM}, the Kalman filter, and the ℓ_2-norm MHE (with one horizon step) can be tuned to give equivalent results for this single measurement case. Table 1.1 shows the tuning values that make each of the estimators equivalent for this example case and in general. In addition to noise, real data often contains outliers.

Table 1.1 Estimator Configuration Values

Estimation Method	Example Tuning	Equivalent Tuning for One Measurement
Filtered Bias Update	$\alpha = 0.0951$	Set α equal to the Kalman Gain K
IDF^{TM}	$K_c = 0.0951e-10, \tau_I = 1e-10$	Set $\frac{K_c}{\tau_I}$ equal to the Kalman Gain as $K_c \rightarrow 0$
Kalman Filter	$P_0 = 0.5, Q = 0.01, R = 1.0$	Set $P_0 = P_\infty$ for equivalency to other methods during initialization
ℓ_2-Norm MHE	Horizon = 50, $Q_y = 100$, $Q_d = 10$	For linear systems with quadratic objective ℓ_2-norm MHE reduces to Kalman Filter [29]
ℓ_1-Norm MHE	Horizon = 50	The ℓ_1-norm MHE does not have equivalent tuning correlations to the other methods

Outliers do not typically fit a standard normal distribution but are instead drastic deviations from normal variation in the data. Outlier detection and removal is typically accomplished by setting rate of change limits, upper validity limits, and lower validity limits. This gross error detection eliminates many but not all of the data outliers. The effect of data outliers is shown in Figure 1.11 with the introduction of two outliers at cycle 50 and cycle 100. The results with data outliers clearly indi-

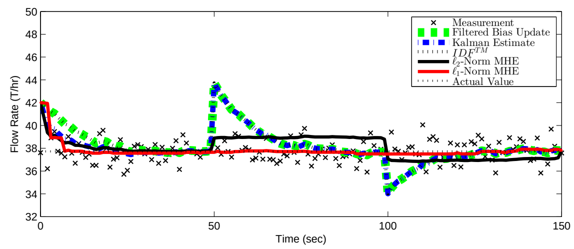

Fig. 1.11 Outlier effect on the filtered bias update, IDF^{TM}, the Kalman filter, ℓ_2-norm MHE, and ℓ_1-norm MHE. Two outliers at cycle 50 (measured flow = 100 T/hr) and cycle 100 (measured flow = 0 T/hr) are introduced to demonstrate the ability of the methods to reject outliers. The ℓ_1-norm MHE is least sensitive to data outliers.

cates that all state estimates, except the ℓ_1-norm MHE, are significantly affected by the bad data points. The insensitivity to bad data is a key advantage of the ℓ_1-norm MHE approach.

1.5 Concluding Remarks

There is a recent increase in data availability in the oil and gas industry due to advances in technology, improved networking, and regulatory requirements that require additional monitoring. When measurements are viewed individually they provide insight into the true state of the process, but do not offer a holistic view of the process. When combined with a process model, the data provides an increased understanding of unmeasured disturbances or unmeasured states. This alignment of measurements and model predictions is accomplished with a variety of techniques ranging from a simple bias update to large-scale optimization approaches. Two optimization approaches discussed in this chapter include Moving Horizon Estimation (MHE) with ℓ_1 and ℓ_2-norms. Efficient solution of the MHE approach is important for solving large-scale problems of industrial significance. Simultaneous solution of the objective function and model equations is a popular approach to solving large-scale models for the data reconciliation.

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Nomenclature

α	Filter Factor for Additive Bias
$\overline{P}$	Predicted Covariance Matrix
$\overline{x}$	Predicted State Vector
ΔP_v	Differential Pressure
$\hat{d}$	Prior Values of the Parameters or Disturbances
$\hat{y}$	Vector of Prior Model Values at the Sampling Times $(\hat{y}_0, \ldots, \hat{y}_n)^T$
Φ	Objective Function Value
σ_q	Standard Deviation of State Noise
σ_r	Standard Deviation of Measurement Noise
τ	Time Constant
τ_I	Integral Time Constant for IDF^{TM}
$\tilde{\delta}$	Innovation: Comparison of Model to Measurements
A	State Transition Matrix
B	Control Matrix
b	Additive Model Bias
C	Observation Matrix
c_L	Slack Variables to Penalize Model Value Changes Below the Prior Value
c_U	Slack Variables to Penalize Model Value Changes Above the Prior Value
C_v	Constant Relating Valve Position to Flow
d	Model Parameter or Disturbance Vector
e_L	Slack Variables to Penalize Model Values Below the Measurement Dead-Band
e_U	Slack Variables to Penalize Model Values Above the Measurement Dead-Band
f	Differential Equation Residuals
$f(l)$	Valve Lift Function
g	Output Function Residuals
g_s	Specific Gravity
h	Inequality Constraint Residuals
I	Integral Term in IDF^{TM}
K	Kalman Gain: Moderate the Measurement Correction

K_c	Proportional Tuning Constant for IDF™
n	Sampling Time Index
PV	Process Variable
Q	Estimated Process Error Covariance
q	Flow Rate (T/hr)
Q_d	Weighting Matrix on Changes of the Disturbance Variables
Q_y	Inverse of the Measurement Error Covariance
R	Estimated Measurement Error Covariance
S	Innovation Covariance: Comparison of Real Error to Prediction
SP	Setpoint
u	Model Input Vector
w_m	Vector of Weights on the Model Values Outside a Measurement Dead-Band
w_p	Vector of Weights to Penalize Deviation from the Prior Solution
x	Model State Vector
x_0	Vector of Initial States
y	Vector of Model Values with Corresponding Measurements
z	Vector of Measurements
IDF™	Implicit Dynamic Feedback
APC	Advanced Process Control
BHA	Bottom Hole Assembly
EKF	Extended Kalman Filter
MHE	Moving Horizon Estimation
MPC	Model Predictive Control
MPD	Managed Pressure Drilling
MPU	Model Parameter Update
NLP	Nonlinear Programming
PI	Proportional Integral Controller
RTO	Real Time Optimization
SISO	Single Input-Single Output
UKF	Unscented Kalman Filter