Chapter 1
Advanced Process Monitoring

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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 information into relevant and actionable information. Methods include a filtered bias update, Internal Dynamic Feedback, Kalman Filtering, Moving Horizon Estimation, and Advanced Process Monitoring. 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 com-

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munication where 3-45 bits per second could be transmitted from the BHA to the 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. This increase in information allows

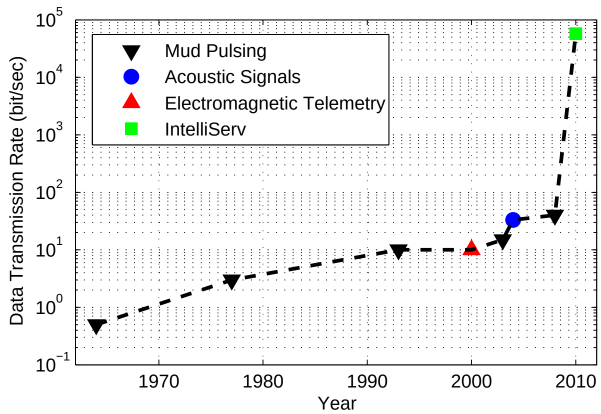

Fig. 1.1 Best available data transmission rates in upstream drill strings [15] [13]. The recent increase in throughput and bi-directional communication has created a new opportunity for better utilizing the information. Without interpretation, the increased data does not necessarily lead to increased 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 occuring 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, Internal Dynamic Feedback, Kalman Filtering, Moving Horizon Estimation, and Advanced Process Monitoring.

Moving Horizon Estimation (MHE) and Advanced Process Monitoring (APM) are optimization approaches that align 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 [31] 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 of production systems [16]. In particular, deep-sea pipeline monitoring poses a challenge due to the remote environment, intermittent weather incidents, and gradual fatigue factors. 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 [5]. On the second to minute time-scales, Model Predictive Control (MPC) applications implement the steady-state targets.

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). Related to process optimization is the activity of process modeling. During the lifecycle of a production 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

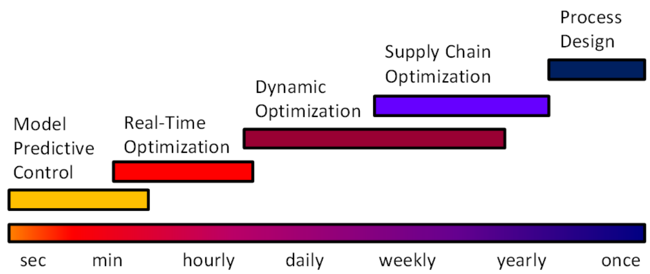

Fig. 1.2 Time-scales of optimization technologies applied in oil and gas industry.

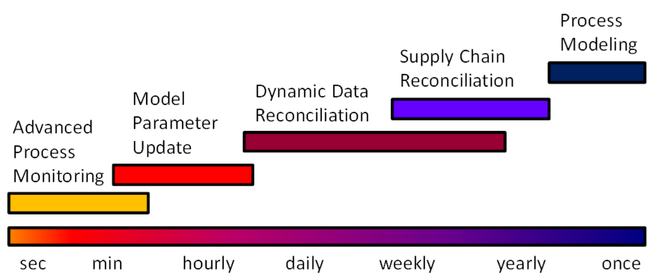

Fig. 1.3 Time-scales of measurement reconciliation applied in the oil and gas industry.

to align a model to the available inventories, capacities, and constraints [17]. Dynamic data reconciliation is used for large-scale dynamic models over long time horizons [18] [19] [33]. It is used in conjunction with dynamic optimization to align the model parameters with dynamic data [29]. For RTO applications, a precursor step is to adjust fouling factors, tray efficiencies, and other parameters with a Model Parameter Update (MPU) [5]. 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, Advanced Process Monitoring (APM) or Moving Horizon Estimation (MHE) are multi-variable approaches for optimal measurement reconciliation in a dynamic model [27]. APM and MHE applications are typically performed on a time-scale faster than that of the process time constant of interest. Both typically execute 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 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 a more fundamental understanding of a process.

1.2 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 [24]. However, simpler control applications such as PID controllers are often preferred in particular situations. Measurement reconciliation also ranges from simple to complex [30]. Simple techniques include filtered bias updates or Implicit Dynamic Feedback (IDF^{TM}). More complex strategies include Kalman filtering, Moving Horizon Estimation (MHE), and Advanced Process Monitoring (APM). Each of these techniques are discussed below.

1.2.1 Filtered Bias Update

A predominant approach for measurement feedback into many of the popular APC commercial packages continues to be a filtered bias update [24]. 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 d is updated at iteration $k+1$ with a filter α as shown in Equation 1.1

$$d_{k+1} = \alpha\left(y_s - y_m\right) + \left(1-\alpha\right)d_k \quad 0 \leq \alpha \leq 1 \tag{1.1}$$

In this case, the difference between the measured state y_s and the predicted model y_m 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

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.

1.2.2 *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 preceeding 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 (y_s)and model state (y_m). The output is an unmeasured disturbance variable (d) of the model. This disturbance variable is adjusted proportional to the current and integrated measurement error as shown in Equation 1.2.

$$
\begin{aligned}
d =& K_c\left(y_s - y_m\right) + \frac{K_c}{\tau_I}\int_{t=0}^{T}\left(y_s - y_m\right)dt \\
d =& K_c\left(y_s - y_m\right) + \frac{K_c}{\tau_I}I, \quad \frac{\partial I}{\partial t} = \left(y_s - y_m\right)
\end{aligned}
\tag{1.2}
$$

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 affect 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. 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

IDF™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™is limited to a past horizon length of one, pairing of only one measurement to one disturbance, and the inability to handle constraints.

1.2.3 Kalman Filter

With a Kalman filter, sequential measurements are used to obtain the state of the system versus a single measurement. These horizon of measurements are combined mathematically to generate the system's state at the current time. As an example application, consider the problem of determining the flow of mud through a drilling pipe. A flow transmitter samples the flow within a few percent of the actual flow. The flow measurement has noise, meaning that the readings have some error that randomly fluctuates around the true flow. The flow can also be estimated from the valve position and differential pressure across the valve. This model update uses other measurements such as pump speed or valve position to infer the desired measured value, such as $\tau \frac{\partial q}{\partial t} + q = C_v f(l) \sqrt{\left(\frac{\Delta P_v}{g_s}\right)}$. Model updating will typically provide a smooth estimate of the flow, but may drift over time. The flow across the valve is expected to follow the relationship that was obtained by characterizing the valve (see Figure 1.4). 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 compressible fluid. Not only is a new flow estimate calculated, but a new covariance is calculated as well as shown in Figure 1.5. The inverse of the covariance is used to tune the Kalman filter. This tuning is essential for optimizing the update phase. In the update phase, a measurement of the flow is taken from the transmitter. Because of the noise, this measurement has a certain amount of uncertainty. The calculated covariance 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 measuremnet. The Kalman filter is optimal for unconstrained, linear systems subject to known normally distributed state and

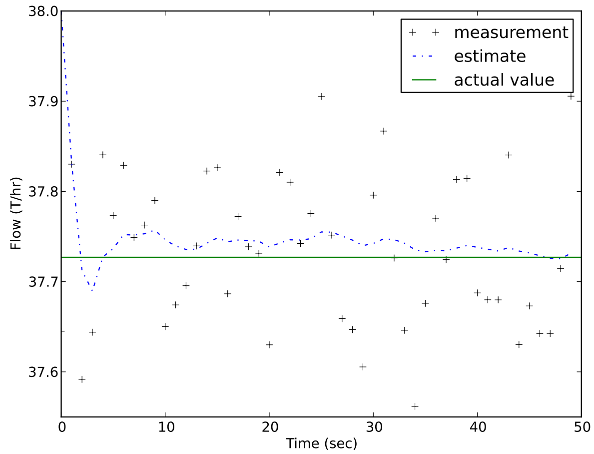

Fig. 1.4 The Kalman filter uses two phases, predict and update, to obtain an estimate of the true flow. During the predict phase, the model calculates an updated flowdue to the latest reported model inputs. During the update phase, part of the flow measurement is used to update the state, inversely proportional to the covariance of the measurement error.

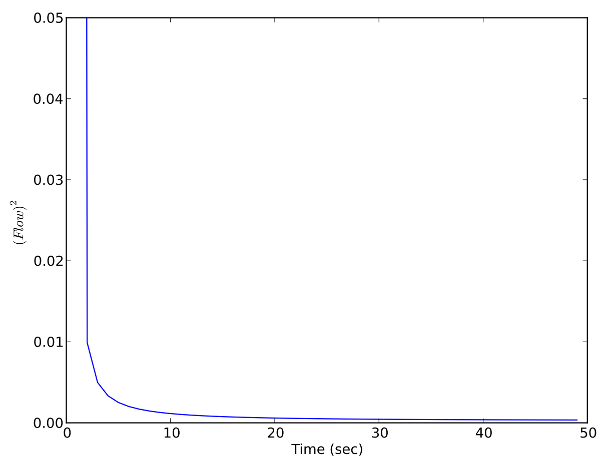

Fig. 1.5 The covariance of the measurement error decreases as additional measurements arrive.

measurement noise [7]. For nonlinear or constrained systems, other techniques are better suited to providing an estimate of the true system state.

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

The Extended Kalman Filter (EKF) is an extension of the Kalman filter for nonlinear systems [2]. 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 [32].

1.2.4 Moving Horizon Estimation

Moving Horizon Estimation (MHE) outperforms the Extended Kalman Filter in the presence of constraints [7]. Recent advances in computational capability and methods have improved the application of MHE to large-scale industrial systems [26]. Just as APC has demonstrated significant benefits by considering multi-variate relationships, MHE is better able to utilize measurements and deliver a more accurate description of the current state of the process and disturbances [28].

By using an optimization framework the model and measurement values are aligned and present detailed information about the production 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 [20] [23] [22]. 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 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 [21]

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 [26].

$$\begin{aligned} \min_{d} \Phi = & \left\| \frac{y_s - y_m}{y_m} \right\|_{Q_y}^2 + \left\| d - \hat{d} \right\|_{Q_d}^2 \\ \text{s.t.} \quad & 0 = f(\dot{x}, x, u, d) \\ & 0 = g(y_s, x, u, d) \\ & a \geq h(x, u, d) \geq b \end{aligned} \tag{1.3}$$

in which

- subscript s refers to sample values
- subscript m refers to model values
- Φ is the objective function value
- y_s is a vector of measurements at all nodes in the horizon $(y_{s,0},\ldots,y_{s,n})^T$
- y_m is a vector of model values at the sampling times $(y_{m,0},\ldots,y_{m,n})^T$
- Q_y is optimally 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 previous unmeasured disturbances
- Q_d is a matrix for the weight on changes of disturbance variables
- g is an output function
- h is an inequality constraint function
- a and b are lower and upper limits, respectively

A graphical representation of the MHE L_2-norm reconciliation is shown in Figure 1.6. The objective for this measured value is a quadratic function with the minimum target between the previous model and measured values. The full estimation problem allows violation of the state constraints [28]. State equality constraints are relaxed and violations are penalized in the objective function. Without d the optimization problem found in Equation 1.3 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.

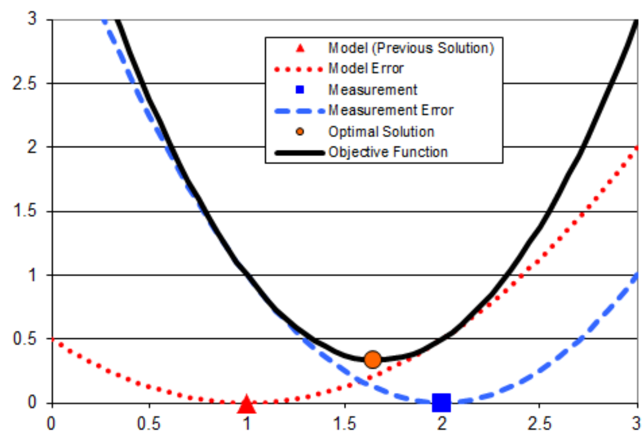

Fig. 1.6 Graphical representation of the L_2-norm for a single measurement in the horizon.

1.2.5 Advanced Process Monitoring

A new form of the estimation problem has been used in industry for a number of years that overcomes some of the limitations of the MHE approach [9]. The objective function in Equation 1.4 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.

$$\begin{aligned}
\min_{d} \Phi &= w_m^T (e_U - e_L) + w_p^T (c_U + c_L) \\
\text{s.t.} \quad & 0 = f(\dot{x}, x, u, p, d) \\
& 0 = g(y_s, x, u, d) \\
& a \geq h(x, u, d) \geq b \\
& \\
& e_U \geq y_s - y_U \\
& e_L \geq y_L - y_s \\
& c_U \geq y_s - \hat{y}_m \\
& c_L \geq \hat{y}_m - y_s \\
& e_U, e_L, c_U, c_L \geq 0
\end{aligned} \tag{1.4}$$

in which

- subscript s refers to sample values
- subscript m refers to model values
- Φ is the objective function value

- y_s is a vector of measurements at all nodes in the horizon $(y_{s,0},\ldots,y_{s,n})^T$
- y_m is a vector of model values at the sampling times $(y_{m,0},\ldots,y_{m,n})^T$
- y_m is a vector of previous model values at the sampling times $(\hat{y}_{m,0},\ldots,\hat{y}_{m,n})^T$
- 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
- a and b are lower and upper limits, respectively
- e_U is a slack variable to penalize model values above the measurement dead-band
- e_L is a slack variable to penalize model values below the measurement dead-band
- c_U is a slack variable to penalize model value changes above the previous value
- c_L is a slack variable to penalize model value changes below the previous value

A graphical representation of the APM L_1-norm reconciliation is shown in Figure 1.7. 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 1.7, 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 previous model value. The APM L_1-norm objective

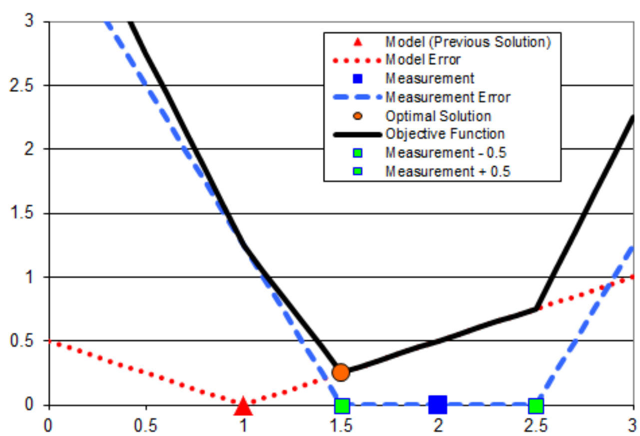

Fig. 1.7 Graphical representation of the APM L_1-norm for a single measurement in the horizon.

has a number of advantages and challenges compared with other methods such as the Kalman filter or MHE. The next sections details the trade-offs with APM.

1.2.5.1 APM Advantages

An important APM 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 APM, 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 APM 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 APM 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 the objective function:

Advantages of APM

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

1.2.5.2 APM Challenges

The challenges with the APM L_1-norm optimization problem include increased complexity and size. Although the APM 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 APM challenges are due to the increased complexity in the solution techniques. Commercial and academic software has been developed to meet this challenge. One software package that our group is developing is the APMonitor Modeling Language [8]. It allows users to focus on the modeling tasks while leaving the implementation details to the software. Filtered bias updating, Kalman filtering, IDF^{TM}, MHE, and APM can be implemented in this web-services platform through interfaces to GNU Octave, MATLAB, or Python.

1.3 Numerical Solution with Dynamic Models

The approach taken in this chapter is simultaneous solution of the model equations and objective function. A general model form consists of nonlinear differential and algebraic equations (DAEs) in open equation format as shown in Equation 1.5.

$$\begin{aligned} 0 &= f\left(\frac{\partial x}{\partial t}, x, u, p, d\right) \\ 0 &= g(y_s, x, u, d) \\ a &\geq h(x, u, d) \geq b \end{aligned} \tag{1.5}$$

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 calcuated set of disturbances $d = (d_0, d_1, \ldots, d_{n-1})$. In Figure 1.8, 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

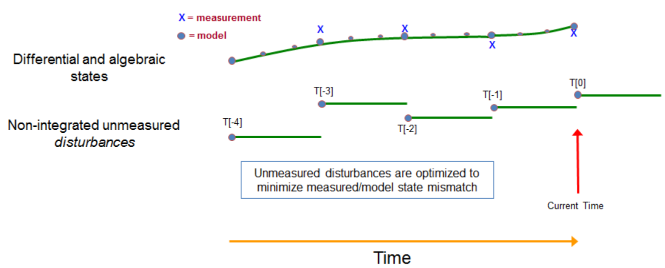

Fig. 1.8 Dynamic equations are discretized over a time horizon and solved simultaneously.

system is accomplished by converting the differential terms to algebraic equations with orthogonal collocation on finite elements [4] or also known as direct transcription [6]. 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 [18] [1]. Other methods include the direct shooting approaches [14] or the explicit solution [25] [12] for simplified problems. The difference between competing implicit solution techniques is how the state equations are satisfied. Direct single or mulitple 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].

1.4 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 wholistic 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) and Advanced Process Monitoring (APM). Efficient solution of MHE or APM approaches 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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