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Event-Trigger Dynamic State Estimation for Practical WAMS Applications in Smart Grid

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To Fiona and Little Lybao, lights of my life

Preface

In the past decade, with the wide deployment of distributed energy resources (DERs), power system is envisioned to be *Smart Grid*, which is expected to be planned and operated in a smart response to a variety of stochastic and intermittent characteristics at multiple time scales. Because the applications are the prime concerns, it often turns out that the particular planning and control applications have always gained widespread focus long before the monitoring has been well developed, which plays an important role in providing the necessary information for the post-processing. However, the monitoring for conventional power system still heavily relies on the steady state model of the system, which rarely occurs in reality with the deep penetration of DERs since there exist a variety of stochastics in both demand side and generation side. As a result, the SCADA systems in energy management systems (EMS), which is dependent on the steady state assumption and no timestamps, cannot accurately capture the dynamics so as to fail the system planning, operation, and control in some complex occasions. To address this issue, the recent phasor measurement units (PMUs) facilitate the dynamics state estimation (DSE) application for wide-area measurement system with its high sampling rate up to 150 Hz. Therefore, it can help the event detection of oscillation, monitoring under extreme event, enhance the hierarchical decentralized control for DERs, and improve the fault detection without any a priori protection replay actions.

Despite the locally available dynamic state information for the decentralized control or the remote available for the centralized control, the DSE application in WAMS relies on the advanced communication infrastructure in power system. However, considering the situation of nowadays that there are over 2000 production-grade PMUs installed across the USA and Canada, which streams data and provides almost 100% visibility into the bulk power system, the dynamics recorder functionality of PMUs definitely boosts the data transmission for local control and protection action or to the remote in communication infrastructure, finally causing the network congestion with the booming size of smart grid. The power

system engineers cannot always broaden the communication bandwidth to meet this endless requirement. Therefore, it is of significance to include the limitation of communication bandwidth into consideration in advance through the event triggered technique. Besides, as the field of PMU and communication infrastructure gain maturity, the quest for better design, functionality, and reliability of DSE application has made it necessary for engineers to design and thoroughly analyze an accurate and robust DSE under all practical communication environment. For example, the packet dropout, a phenomenon characterized by the fail of measurement receiving in the remote via the transmission network, leads possibly to the misunderstanding by the remote center together with the event triggered filtering, which has no explicit idea on whether the measurement is received or lost. Therefore, knowing *how* (in what design) and *when* (under what conditions) an event triggered filtering for DSE application accurately and stably work should be of fundamental importance. Such knowledge, however, requires the appropriate design and in-depth analysis on its numerical stability.

This book is concerned with the development and design oriented analysis of event triggered dynamic state estimation for practical WAMS applications. The objective is to provide a systematic treatment procedure for communication reduction, filtering design, and stability analysis of the DSE application in WAMS. The essential techniques for filtering with event triggered sampling strategy are given step by step and proved, along with the practical application examples describing the key procedure for strategy implementation integrated into the filtering design. The target audience includes graduate students, academic researchers, and engineers in industry who work in the field of DSE for WAMS application and have the development need to reduce the communication burden and guarantee the DSE accuracy in WAMS. Furthermore, in presenting various DSE filtering design, a conscientious effort has been made to emphasize the practical implementation using pseudo-code rather than only the mathematical abstraction. We hope this book can also be useful as a design guideline for graduate students and academic researchers who wish to grasp the essentials to design the DSE application for practical WAMS in order to reduce the communication burden, as well as a readable reference for engineers in industry who wish to implement such practical DSE.

We begin in Chap. 1 with an overview of the WAMS constitution and its DSE application, and an outline of some practical concerns for application. In Chap. 2, in order to build the fundamental knowledge of event triggered based DSE, various event triggered sampling strategies and its advantageous features are given for linear filtering design. Besides, as a performance reference, the intermittent Kalman filtering is also designed, which is also targeted at the filtering for communication reduction. Furthermore, the simplest nonlinear Kalman variant, i.e., the extended Kalman filter, together with the event triggered strategy is designed for the brief demonstration of DSE implementation. However, its performance greatly suffers from the practical nonlinearity of power grid, which therefore initiates the subsequent research journey of this book for the sake of practical application. In Chap. 3, an event triggered cubature Kalman filter (ETCKF) is proposed to reduce the amount of data transmission while ensuring the estimation accuracy. The ETCKF uses the

innovation based event triggered sampling strategy in the sensor node to reduce the data transmission. Based on the developed nonlinear event triggered strategy, the cubature Kalman filter (CKF), using the third-degree spherical-radial cubature rule, is adopted to further ensure the estimation accuracy. Further, the stochastic stability of ETCKF is analyzed. Using the stochastic Lyapunov stability lemma, ETCKF is proven to be stochastically stable if a sufficient condition, which is composed of offline parameters, is satisfied. Moreover, the average communication rate of ETCKF is derived, which is only related to design parameters in innovation condition. To satisfy the determined arrival rate need of the limited channel capacity, an event triggered particle filter is accordingly designed in Chap. 4. An arrival rate guaranteed event triggered strategy is established by utilizing Monte Carlo method to approximate the prior conditional distribution of observations. Moreover, an ET-PF filtering algorithm is further proposed by making full use of the information from the event triggered strategy to enhance the performance of estimation. Under the constraints including both the communication and computation power at sensor nodes, an event triggered heterogeneous nonlinear Kalman filter (ET-HNF) is designed in Chap. 5. The ET-HNF utilizes the unified filtering of unscented transformation with PF theories so that both the accuracy and the relief of communication burden can be guaranteed. An unscented transformation based event triggered UKF (ET-UKF) is firstly designed to supply the event triggered strategy. Furthermore, a Monte Carlo based filtering algorithm is designed in the estimation center to provide the accurate filtering results. To deal with the non-Gaussian or unknown noises, Chap. 6 designs the stochastic event triggered robust cubature Kalman filter (SETRCKF). Firstly, to make up for the deficiency of ETCKF, the stochastic event triggered cubature Kalman filter (SETCKF) is proposed using the stochastic innovation based event triggered sampling strategy, which can maintain the Gaussian property of the conditional distribution of the system state. Based on SETCKF, the SETRCKF is further designed by using the moving-window estimation method and the adaptive method to estimate the measurement noise covariance matrices and the process noise covariance matrices and using the Huber function to make SETCKF more robust. Moreover, the stochastic stabilities of the two proposed filters are analyzed by deriving the sufficient conditions regarding the stochastic stability of the filtering error. To tackle the presence of packet dropout when using the stochastic innovation based event triggered sampling strategy, Chap. 7 proposes the stochastic event triggered cubature suboptimal filter (SETCF). Firstly, by modeling the packet dropout as a Bernoulli process and inspired by the linear suboptimal filter, the cubature suboptimal filter (CF) is designed for periodic sampling system. Based on CF and the stochastic innovation based event triggered sampling strategy, SETCF is proposed. Moreover, the stochastic stability of the two proposed filters is analyzed by using the Lyapunov stability lemma. Considering that CPS is vulnerable to cyber attack and has limited bandwidth, the event triggered cubature Kalman filters under two typical attack types, which are the data tampering attack and the deviation control command forgery attack, are established in Chap. 8, respectively. Aiming at the data tampering attack problem, the anomaly data detector is designed by using the projection statistics method. After the attack is discovered, the weight

matrix is constructed by using the detection result to correct the measurement value to ensure the filtering accuracy, which completes the filter design. For the deviation control command forgery attack problem, the problem is firstly transformed into the problem that the system is with unknown input. Then, the Bayesian inference method is used to derive the event triggered cubature Kalman filtering algorithm. The feasibility and performance of all the developed filterings are verified based on the IEEE 39 bus system.

For the successful completion of this book, I highly appreciate a number of people, institutions, and organizations. First of all, in the course of my research in this field, I have constantly collaborated and been inspired with my former students, among which I am indebted to Dr. Sen Li, Dr. Luyu Li, and Bin Liu for their diligent work regarding the theoretical derivation and practical implementation as well as critical challenge to my knowledge making me pay specific attention to some easily overlooked problems but finally great findings. I also wish to give my sincere appreciation to Dr. Xi Chen, Prof. Tyrone Fernando, and Prof. Xiangdong Liu, who helped me a lot along the research in this field and their experienced advisory. Furthermore, Dr. Junbo Zhao deserves my grateful thanks due to our discussion on the research of DSE. I would also like to thank the staff of the Springer for their professional and constant support of this project.

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Contents

1	Introduction	1
1.1	WAMS System	1
1.1.1	Basic Synchronization Principles of WAMS	3
1.1.2	Phasor Measurement Unit	4
1.1.3	WAMS Control Center	5
1.1.4	Network Communication System	6
1.2	State Estimation of WAMS	6
1.2.1	State Estimation Under Packet Dropout	6
1.2.2	State Estimation Under Network Attack	9
1.3	Development of the Event Triggered Filter	10
1.3.1	Design of Event Triggered Sampling Strategy	11
1.3.2	Design of Event Triggered Filtering	12
1.4	Development of Nonlinear Filtering	14
1.4.1	Nonlinear Filtering Based on Taylor Expansion Approximation	15
1.4.2	Nonlinear Filtering Based on Deterministic Sampling	16
1.4.3	Nonlinear Filtering Based on Stochastic Sampling	19
2	Event Triggered Sampling Strategies	21
2.1	Event Triggered Sampling Strategy	21
2.1.1	Deterministic Event Triggered Sampling Strategy	22
2.1.2	Stochastic Event Triggered Sampling Strategy	25
2.1.3	Comparisons of Event Triggered Sampling Strategy	27
2.2	Event Triggered Linear Filter	27
2.2.1	Innovation Based Event Triggered Kalman Filter	29
2.2.2	Stochastic Innovational Event Triggered Kalman Filter	30
2.2.3	Intermittent Kalman Filter	31
2.3	Event Triggered Extended Kalman Filter Design for Nonlinear System	32
2.3.1	ET-EKF Design	32

2.3.2	IEEE 39 Buses Simulation Platform	35
2.3.3	Simulation Verification for ET-EKF	38
2.4	Conclusions	43
3	Event Triggered CKF Using Innovation Based Condition	53
3.1	Introduction	53
3.2	Cubature Kalman Filter	54
3.2.1	Gaussian Filter	55
3.2.2	Spherical-Radial Cubature Integral	57
3.2.3	Cubature Kalman Filter	58
3.3	CKF Using Innovation Based Condition	59
3.3.1	Design of Event Triggered Sampling Strategy	60
3.3.2	Design of Remote Filter	61
3.4	Stochastic Stability Analysis of ETCKF	65
3.4.1	Boundedness of the ETCKF Posterior Variance Matrix	67
3.4.2	Error Boundedness Analysis for the ETCKF	71
3.5	Simulation and Verification	74
3.5.1	Comparison of Filtering Dynamic Performance with Different δ	75
3.5.2	Comparisons of Estimation Error under Different δ Values ..	75
3.5.3	Verification on Stability and Arrival Rate	80
3.5.4	Simulation on Communication Delay	83
3.6	Conclusions	84
4	Event Triggered Particle Filter Using Innovation Based Condition with Guaranteed Arrival Rate	87
4.1	Introduction	87
4.2	Monte Carlo Method and Its Application in Nonlinear Filtering	88
4.2.1	Monte Carlo Method	88
4.2.2	Application of Monte Carlo Method in Nonlinear Filtering ..	90
4.3	Design of Event Triggered Particle Filter with A Guaranteed Arrival Rate Based on Monte Carlo Method	93
4.3.1	Design of Triggered Strategy with A Guaranteed Arrival Rate	93
4.3.2	Filtering Design Using Triggered Information	98
4.4	Simulation of ET-PF for DSE in WAMS	105
4.5	Conclusions	115
5	Event Triggered Heterogeneous Nonlinear Filter Considering Nodal Computation Capability	119
5.1	Introduction	119
5.2	System Design of Heterogeneous Event Triggered Nonlinear Filter ..	121
5.3	Design of Slave Filter Based on Event Triggered UKF	123
5.3.1	UT Transformation	123
5.3.2	Event Triggered Sampling Strategy	125
5.3.3	Design of Event Triggered UKF	127

- 5.4 Master Filter and Its Cooperation with the Slave Filter 130
 - 5.4.1 Monte Carlo Based Master Filter Design 130
 - 5.4.2 Cooperation Between Master and Slave Filters at Control Center 134
- 5.5 Simulation and Verification on ET-HNF 136
- 5.6 Conclusions 143
- 6 Event Triggered Robust Cubature Kalman Filter Using Stochastic Innovational Condition 149**
 - 6.1 Introduction 149
 - 6.2 Design of Event Triggered Cubature Filter Using Stochastic Innovational Condition 150
 - 6.2.1 Design of Event Triggered CKF Using Stochastic Innovational Condition 150
 - 6.2.2 Filtering Design at the Control Center 152
 - 6.3 Design of Event Triggered Robust Cubature Kalman Filter Using Stochastic Innovational Condition 157
 - 6.3.1 Event Triggered Strategy Design for SETRCKF 157
 - 6.3.2 Filtering Design of SETRCKF 160
 - 6.4 Analysis of Stochastic Stability of Event Triggered Filtering Using Stochastic Innovational Condition 163
 - 6.4.1 Stochastic Stability Analysis for SETCKF 163
 - 6.4.2 Stochastic Stability Analysis for SETRCKF 166
 - 6.5 Simulation and Verification 169
 - 6.5.1 Verification on SETCKF Filtering Performance 169
 - 6.5.2 Verification on SETRCKF 180
 - 6.6 Conclusions 187
- 7 Event Triggered Suboptimal CKF Upon Channel Packet Dropout 189**
 - 7.1 Introduction 189
 - 7.2 Design of Suboptimal CKF Under Channel Packet Dropout 190
 - 7.2.1 Suboptimal Kalman Filter Under Channel Packet Dropout .. 191
 - 7.2.2 Design of Suboptimal CKF Under Channel Packet Dropout . 193
 - 7.3 Design of Event Triggered Suboptimal Cubature Kalman Under Channel Packet Dropout 194
 - 7.3.1 Design of Event Triggered Sampling Strategy 195
 - 7.3.2 Design of Filtering at Center 196
 - 7.4 Analysis of Stochastic Stability of Suboptimal Kalman Filter in Case of Channel Packet Dropout 197
 - 7.4.1 Analysis of Stochastic Stability for Suboptimal CKF 197
 - 7.4.2 Analysis of Stochastic Stability of Event Triggered Suboptimal CKF 202
 - 7.5 Simulation and Verification 205
 - 7.5.1 Verification on CF Performance 205
 - 7.5.2 Verification on the SETCF Filtering Performance 217
 - 7.6 Conclusions 234

- 8 Event Triggered Cubature Kalman Filter Subject to Network Attacks** 237
 - 8.1 Introduction 237
 - 8.2 Design of Event Triggered Cubature Kalman Filter Subject to Data Tampering Attacks 238
 - 8.2.1 Design of Abnormal Data Detection Algorithm 239
 - 8.2.2 Design of Event Triggered CKF Filtering Subject to Data Tampering Attacks 241
 - 8.3 Design of Event Triggered Cubature Kalman Filter Subject to Control Command Forging Attacks 243
 - 8.4 Simulation and Verification 252
 - 8.4.1 Verification on Event-Triggered CKF Subject to Data Tampering Attacks 252
 - 8.4.2 Verification on Performances of Event-Triggered CKF Subject to Control Command Forging Attacks 257
 - 8.5 Conclusions 261
- 9 Conclusion** 267
- References** 269
- Index** 277

Nomenclature

Symbol	Description	Symbol	Description
\equiv	Identically equal to	$\ A\ _F$	The Frobenius norm of real matrix A
\triangleq	Defined as	$A > 0$	The positive definite matrix A
\forall	For all	$A \geq 0$	The positive semi-definite matrix A
\exists	Exists	$A > B$	The matrix $(A - B)$ is positive definite
\rightarrow	Approach to	$A \geq B$	The matrix $(A - B)$ is positive semi-definite
\in	Belongs to	$A \oplus B$	The block diagonal matrix whose diagonal elements are A, B
\notin	Doesn't belong to	$\text{diag}[x_1, \dots, x_n]$	The diagonal matrix whose diagonal elements are $\{x_1, \dots, x_n\}$
\subset	Subset	$A^{1/2}$	The lower triangular matrix of Cholesky decomposition of A
\cup	Union	$\mathcal{N}(x, P)$	The Gaussian distribution with x as mean and P as variance
Σ	Sum	$\mathbf{1}_{(p)}$	The p -dimensional vector with all one
$\exp(x)$	Exponential function of x	$\mathbf{0}_{(p)}$	The p -dimensional vector with all zero
\max	Maximum	I_m	The identity matrix with dimension m
\min	Minimum	$\delta(x)$	Dirac function
∞	Infinity	$x^i \leftarrow p(x)$	The particle point x^i following the distribution of $p(x)$

Symbol	Description	Symbol	Description
\mathbb{R}^n	n -dimensional column vector set	$\mathcal{X}^{(i)} \leftarrow \mathcal{N}(x, P)$	The Sigma point \mathcal{X} following the distribution of $\mathcal{N}(x, P)$
$\mathbb{R}^{m \times n}$	$m \times n$ real matrices	$x \sim p(x)$	The random variable x follows the distribution of $p(x)$
$\mathbb{E}(x)$	The estimation of x	$p(x)$	The distribution of random variable of x
$\mathbf{Cov}(x)$	The covariance of x	$p(x y)$	The condition probability distribution of random number x given y
x^T	The transposition of vector x	$\mathbb{E}(x y)$	The condition expectation of random number x given y
$\ x\ $	The Euclidian norm of real vector x	$\dim(A)$	The dimension of square matrix A
$\ A\ $	The spectral norm of real matrix A	$\text{rank}(A)$	The rank of A

Chapter 1

Introduction



1.1 WAMS System

The development of power system is continuously accompanied with the emergence of new technologies, which ranges from the electrical infrastructure to the informatics. *Smart grid* is envisioned to offer an intelligent, automated, and widespread distributed generation (DG) by a two-way flow of electricity generation/consumption and information exchange. The metering is the fundamental of all the functional applications in power system such as control, analysis, plan, etc. Therefore, the wide-area measurement systems (WAMS) have greater impact on the reliable operation of power system.

As shown in Fig. 1.1, the WAMS consist of the control center, time synchronization, network communication system, and phasor measurement unit (PMU). The measurement data are collected from stations distributed in different areas, which are equipped with PMUs. In general, the information about the power system can be extracted from its raw data measured by PMU or other data resources by a kind of computer aided tools known as WAMS applications. All the applications in the area control center (for large scale system) or central control center (for small scale system) acquire system data from PMUs or other data resources for dispatching and control purpose via the wire or wireless communication link as shown in Fig. 1.2. And most of them have strict real-time requirement. But with the widespread use of PMUs, a huge amount of data needs to be transmitted even within regions, which may result in communication link congestion and increasing communication latency. Therefore, the state estimation should be specifically designed to deal with the communication constraint.

With the assist of accurate state estimation from WAMS, a scheduling and control center can master all operational data of the grid in a real time and online manner so as to calculate the real-time operating parameters and acquire the online state of the system through state estimation, and simulate the operational states of grid based

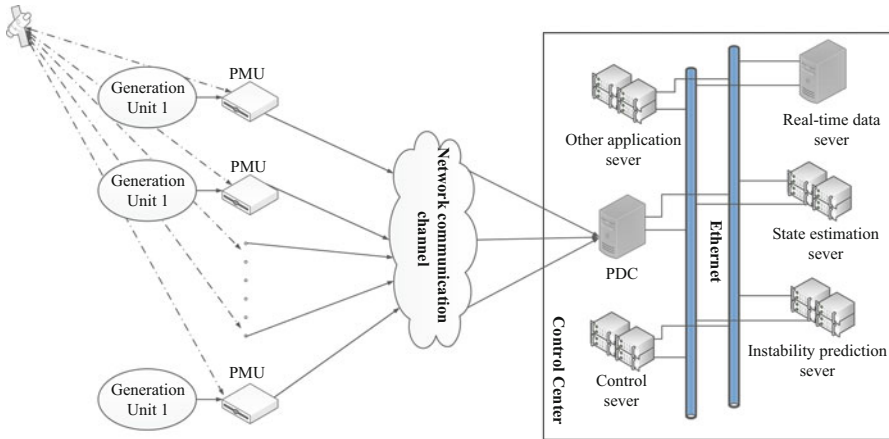


Fig. 1.1 System structure of wide-area measurement system (WAMS) using PMU through network communication media

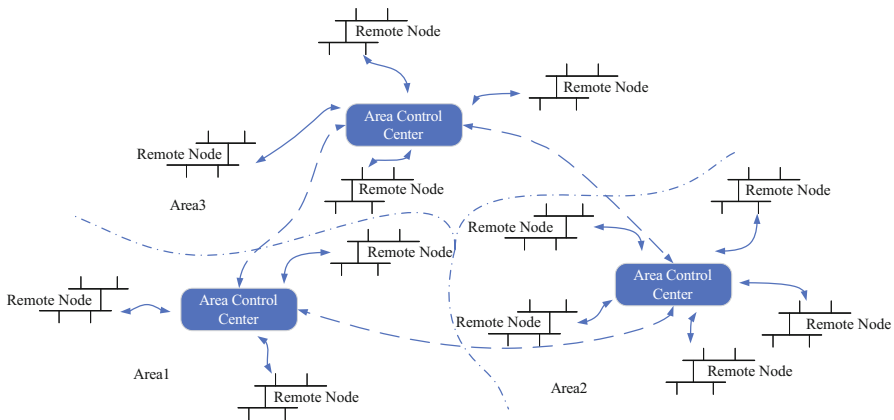


Fig. 1.2 Communication structure of WAMS, whose hierarchical structure is from the area control center to the remote node

on the estimation, and further conduct online stability analysis of the system, and optimize grid scheduling, and finally combine local control and grid scheduling to ensure the reliability and accuracy of the whole system. It also allows the analysis of the local fault through the synchronization of phasor measurement data, and the locating of system's weaknesses. By doing so, the systematic research, analysis, and improvement can be facilitated to avoid recurrence of similar accidents.

1.1.1 Basic Synchronization Principles of WAMS

The WAMS was initially invented to enhance the reliability of the domestic grid of the USA and adjust its electric market. In 1989, WAMS was jointly developed by the Bonneville Power Administration (BPA) and the Western Area Power Administration of the Department of Energy (DOE) and firstly applied in the northwestern power grid. Its main scope of development is to establish the flexible AC transmission system (FACTS) as the core element base for real-time operation monitoring and optimization of the grid, and develop an effective online software package in response to voltage and dynamic safety evaluation issues.

For the synchronization, WAMS must unify their time coordinate so as to establish a time synchronization system. The time coordinate system comprises the beginning timestamp and the scale unit of time (second). The time synchronizing system can be synchronized with the measurement data only when the clock of the synchronous measurement unit in WAMS conforms to the coordinated universal time (UTC). The time synchronizing technologies primarily include long- and short-wave-time transfer time synchronization, internet based time synchronization, satellite time service and digital hierarchy (SDH) network time synchronization, telephone dialing time synchronization, and other technologies. They are effectively applied in different fields of time synchronization and have their respective weaknesses.

1. Long-and-short-wave-time transfer time synchronization. Long- and short-wave-time service technology is commonly used for military and navigational purposes, and it is based on the transmission of radio signals. Its advantages include the simple transmitting and receiving devices, extensive signal coverage, low cost, and real-time calibration of the local clock. Its weakness is the seldom usage in civilian applications.
2. Internet time synchronization. This technology allows the remote calibration of computer clocks via the Internet at an accuracy of 1–50 ms. However, this technology is based on computers and the Internet so that the system safety cannot be guaranteed in a complicated network environment.
3. Digital hierarchy (SDH) network time synchronization. This technology utilizes the feature in synchronization between time code and clock so as to add the time code signals into the unused bytes of SDH or SONET-STM-N multiplex section overhead (MSOH). The whole coded signals satisfy the frame structure required in ITU-TG.708 with a length setting of 5 bit. This technology enables the long distance and highly accurate transmission in the scale of 100 ns. Its weaknesses are the frequent hardware maintenance, which hinders its own development in power system.
4. Telephone dialing time synchronization. Telephone dialing time synchronization is not a high technology and can be completed via a computer or some synchronization software with the help of a telephone wire, modem, or other common communication devices. However, this technology offers very poor real-

Table 1.1 Time accuracy for various synchronization techniques

Time synchronization technique	Long-and-short-wave	Internet	SDH	Telephone	GPS
Accuracy	1–10 ms	1–50 ms	100 ns	100 ms	5–100 ns

time performance. Even if the transmission delay caused by part of the telephone wires is alleviated with the help of feedback technologies, it still cannot satisfy the practical requirement of the complex power system.

5. Satellite time synchronization. The worldwide well developed GPS system extensively applies the satellite time synchronization technology. GPS satellites send out the synchronous signals, and the user can receive the signals transmitted by 24 satellites in orbit and several standby satellites at any place on the earth. These satellites are all equipped with the accurate atomic clocks. If the user's clock and the satellite's atomic clock are synchronized, the navigation time from the satellite to the user can be acquired, and their distance and the current time coordinate can be inferred as well. The advantage of this technology is that the signals synchronized by GPS satellites can be received on a real-time basis and the reliability and high time accuracy can be guaranteed. However, some situations hinder the development of GPS technology. Firstly, the US army controls the time codes of higher accuracy and opens them only to authorized users. Secondly, the high GPS operational requirements disable the wide installation of GPS synchronizing equipment at the power plant with comparatively complex ambient environments.

Table 1.1 lists the comparison of the different time accuracies for different synchronizing technologies. Considering the advantages of different synchronizing technologies mentioned above, the satellite synchronizing technology is the most appropriate for the implementation of accurate and affordable WAMS.

1.1.2 Phasor Measurement Unit

PMU facilitates the widespread application of WAMS. Its main function is firstly receiving the synchronized measurement data and then transmitting these synchronized signals to the scheduling and control center. In a UTC system, the operator on duty analyzes and calculates all system measurement data collected by PMU to acquire the synchronized phasor measurement information. PMU can record the transient data through the triggering mode and the dynamic data through continuous recording. It can be further divided into centralized and distributed mode according to the installment. If there has only one control center to collect the measurement data, the centralized installment of PMUs is preferred. On the other hand, the distributed installment of PMUs is recommended for extensively distributed stations

(e.g., power plant). Finally, the data collector will package the distributed PMU data and transmit them to the master center.

The synchronous phasor measurement of WAMS can link the massive state observations together within a structurally complex power system based on a UTC system.

1.1.3 WAMS Control Center

The hardware system of WAMS's control center includes the communication server, data analysis, historical data server, statement, scheduler workstation, and other equipment. The functions of WAMS control center include the real-time monitoring and management of PMUs, the reception of the real-time measurement data, recording files, event logging, wave recording. The data received from the station are further pre-processed and then sent to the real-time or historical database for the purpose of real-time or offline analysis. Besides, the software system includes the data collection and pre-processing, real-time monitoring system, database system (including real-time and historical data), advanced applications, and internet interface. Figure 1.1 shows the main WAMS applications in the control center. Some modern WAMS applications are as follows [1].

Wide-Area Dynamic Monitoring and Analysis This application can provide various basic tools to observe power grid and form a global and dynamic view of the system.

Instability Prediction Conventionally, the stability analysis of power systems is done offline. But due to the high sample rate of PMU, the real-time stability analysis and instability prediction can be fulfilled.

Generator Operation Status Monitoring This function can provide a close supervision of generators, which is very useful in system operation and stability assessment because it can provide the real-time information of generators.

State Estimation This is the most important WAMS application and is considered as kernel because it can provide extracts creditable data, which is the input of other applications, by eliminating the effect of bad measurements.

The WAMS control center and the conventional SCADA/EMS are interconnected through the network communication via the Internet, the latter of which provides the state estimation to WAMS main station. On the other hand, the WAMS offers the dynamic information of grid to the SCADA/EMS. Moreover, the WAMS control center can also extract the transient data of grid and the relay protection from the fault information management system of SCADA/EMS.

1.1.4 Network Communication System

The network communication system aims at providing the channel for data exchange between its subsystems to ensure its reliable operation, which needs to guarantee the real-time data transmission, particularly in a large scale interconnected network. The principles of the physical structure of a network communication system include that,

1. It should be layered and divided into zones according to the monitored area, i.e., provincial and regional monitoring system and national scheduling and monitoring system, among which the level of these three monitoring and control systems increases successively.
2. Various systems within WAMS keep the bidirectional data exchange through a tree structure.
3. Different WAMS control center and stations can engage in the bidirectional transmission of real-time online data and historical data stored in the database.
4. There is no specific requirement on the control center, which can have the direct exchange with the PMUs of lower levels.

1.2 State Estimation of WAMS

WAMS is typically a cyber-physical system (CPS). As shown in Fig. 1.3, the measurement data needs to be transmitted to the decision-making layer for state estimation via a network, which is mostly via the wireless sensor network (WSN) in WAMS. Therefore, it is necessary to consider the influence of unstable transmission network on system states. Specifically, with the deep penetration of renewable energy to the conventional power system, which is widely installed in rural area, the network communication media can be easily exposed to the interference from environment. Such influence includes the time delay, packet dropout, channel attenuation, network attack, etc. This section specifically provides a general description of the state estimation in case of the packet dropout and network attack.

1.2.1 State Estimation Under Packet Dropout

The packet dropout occurs when the filter on the decision-making level fails to receive the measurement transmitted by the sensor via the transmission network. The causes of packet loss include the physical fault, nodal hardware fault, network congestion, routing error, data packet conflict, etc. The packet dropout cannot be avoided in a communication network, particularly a radio transmission network, where it may occur due to EMI in the environment. If the state estimation is specifically designed for the dropout, the estimation accuracy will decline sharply

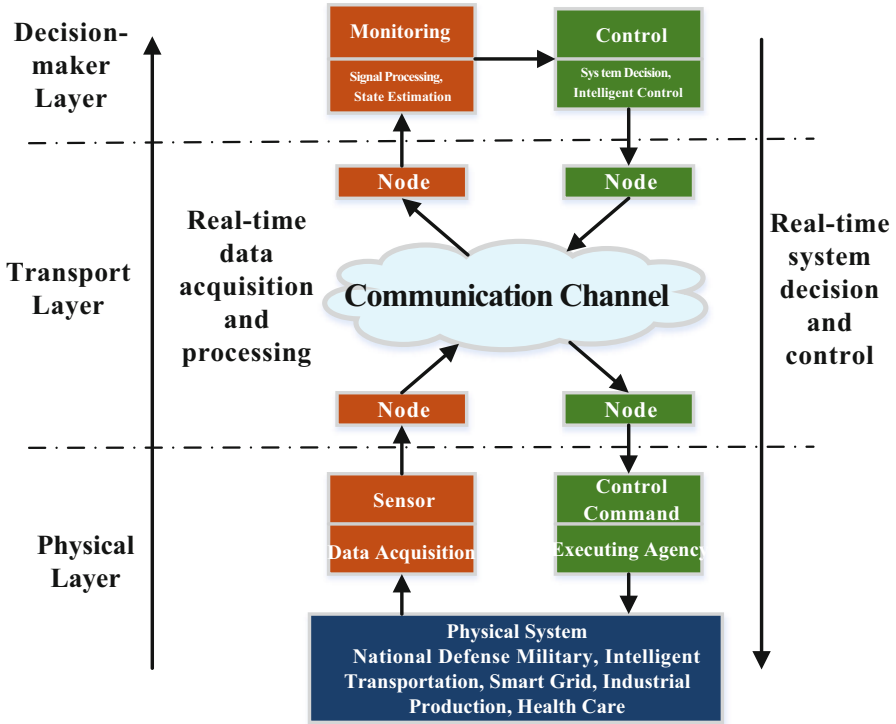


Fig. 1.3 The system diagram of classical cyber-physical system, whose hierarchical structure consists of decision-maker layer, transport layer, and physical layer



Fig. 1.4 The system diagram of intermittent filtering, the performance of which is mainly affected by the communication channel

and the divergence will even occur. Therefore, it is valuable in practice to investigate the state estimation and analyze its accuracy and stability under packet dropout.

Generally, the filtering upon the packet dropout is referred to as the intermittent filtering. The architecture is shown in Fig. 1.4. The research basis for intermittent filtering is the modeling of packet loss. The most commonly used model is Bernoulli stochastic process model subject to i.i.d. (independent identically distribution), whose assumption is that the packet loss in channel at the current time has no dependence with the previous time instance so that the probability of packet loss at each time is identical. Based on this packet dropout model, the stochastic stability of linear intermittent Kalman filter was investigated and the definition of intermittent linear filter stability was pointed out that the estimation of the mean

value of prior variance matrix was stochastically bounded [2]. Furthermore, it was further proved that the intermittent Kalman filter was stochastically stable when the packet loss rate was lower than the critical probability. However, the analytical solution of such critical probability was not given. It was also demonstrated that the analytical solution of such critical probability could be got only when the system's observation matrix was nonsingular. Besides, the solving condition of critical probability was relaxed and the solution could be obtained when the observable subspace corresponding to the system observation matrix has full rank [3, 4].

Except Bernoulli stochastic process to model the packet loss, the other is the homogeneous Markov model, under which the packet loss rate at each time instance is no longer independent but relates to whether the packet loss occurs at previous time instance. Compared with Bernoulli stochastic process, this model can represent more extensive characteristics of channel condition and better fit in with the actual conditions. Based on this model, the stochastic stability issue of intermittent Kalman filter was studied under this model [5], where the mean peak of the prior variance matrix was selected as the evaluation index of stochastic stability and the sufficient conditions for the stochastic stability was given for the filter. The results showed that the peak stability of the Kalman filter for the scalar system was only related to the probability of recovery after the packet loss and there existed a critical recovery probability. Based on this, a stochastic Riccati equation was utilized to infer the more stringent sufficient condition of filter stability [6] than that in [5]. In [7], it was proved that the mean peak stability of the prior variance matrix was equivalent to the mean stability proposed in [2] under certain conditions. Apart from the evaluation index of peak stability above, the mean of posterior variance matrix was proposed in [8] as an evaluation index of stability estimation and more stringent sufficient conditions of stability were derived. The evaluation index of the weak convergence stability of filter was designed in [9] under the Markov process, which proved that the sufficient conditions considering weak convergence were most relaxed through the comparison of the sufficient conditions of filter stability using various evaluation indexes under the homogeneous Markov process.

The aforementioned intermittent filter collects data from a single sensor. However, it is common that data are collected from distributed sensors and transmitted to the decision-making layer via various channels in the CPS system. According to such a scenario, the situation was studied in [10], where two sensors were used for data collection and both transmission channels were described as i.i.d. and Bernoulli stochastic process, and the stochastic stability of the filter was analyzed accordingly. The stability of the intermittent filter under the homogeneous Markov model was investigated when two sensors were used for data collection [11]. However, the previous two methods were inapplicable to the case of multiple sensors. The linear matrix inequality (LMI) equation was utilized in [12] to solve the critical probability of arrival rate for various channels so that the filtering stability was analyzed for the multi-sensor filtering system under packet loss.

The previous research results are obtained based on the linear system. Many researchers have also studied the intermittent filters for nonlinear system. The LMI was utilized to simplify the nonlinear filtering into a multiple linear filtering so as to

analyze nonlinear intermittent filter [13–15]. The stability of intermittent EKF was studied in [16] and the results showed that the stability of nonlinear intermittent filter must use the mean error as the evaluation index. However, there contains online parameters for the sufficient conditions of stability. The sufficient conditions of filtering stability were given for intermittent suboptimal EKF in [17], which only contained offline parameters. A more relaxed sufficient conditions of filtering stability was proposed in [18] based on [16], which can be completely expressed by offline parameters. The stability analysis of intermittent UKF under the Bernoulli stochastic process and the homogeneous Markov process was carried out in [19, 20].

Moreover, some researchers have investigated the state estimation upon the occurrence of packet dropout with other channel conditions. The state estimation under packet dropout and time delay was studied in [21, 22]. Besides, the state estimation upon packet dropout and quantification was considered in [23, 24].

However the previous research focused on the intermittent filtering under the periodic sampling strategy, there is almost no intermittent filtering under the event triggered sampling strategy. Although the event triggered sampling strategy can hinder the packet dropout to one certain extent due to the reduced data transmission, there are various kinds of causes for packet dropout as mentioned above, and not only within the scope of small channel bandwidth and heavy data transmission load. Therefore, it is necessary to design the intermittent filtering under event triggered sampling strategy and analyze its filtering stability.

1.2.2 State Estimation Under Network Attack

The network attack refers to the damage to the measurement data due to an malicious attack on the transmission channel, which includes DoS attack [25], replay attack [26], data injection attack [27], wormhole attack [28], etc. Because the transmission highly relies on the media, the CPS is vulnerable to DoS and data injection attack. Once the network attack occurs, the accuracy of state estimation will be severely affected, and the divergence may even occur. Therefore, many researchers have studied the state estimation under network attack.

Normally, the network attack may be blocked and intercepted by the protection. In other words, the network attack normally occurs on a stochastic basis. Therefore, the state estimation system under network attack is shown in Fig. 1.5. The state estimation of linear system upon data infusion attack was carried out and an attack set was established which would not be discovered by the detector [29]. The data infusion attack issue was studied for smart grid state estimation [30], which showed that the attacker could change the state estimation at any time [31] and Literature [32]. Two safety indexes were set in [31] to evaluate the difficulty of launching a data infusion attack on specific measurements while it was pointed out in [32] that the defense against data infusion attack could be fulfilled through the encryption of a certain number of sensors. Furthermore, the defense mechanism against data injection attack on state estimation was investigated [33], which

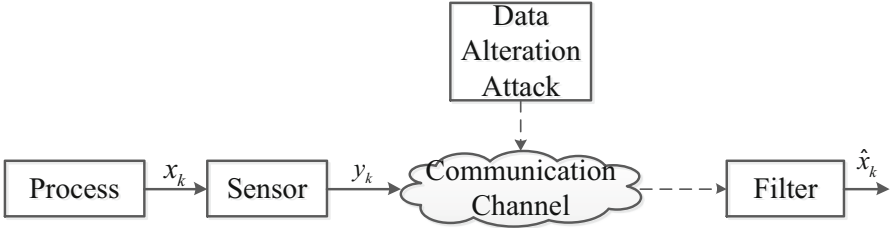


Fig. 1.5 The system diagram of dynamic state estimation under the data alteration attack through the communication channel

proposed the fewest number of nodes to be attacked as the safety index and designed an designation algorithm for encrypted sensor to realize attack defense.

Moreover, an elastic estimator was designed to address the issue of state estimation under a stochastic system hidden attack [34]. The estimation of the initial value of system state was investigated in [35] when some measurements are damaged, which showed that there had relationship between the quantity of recoverable sensors under attack and the existence of the decryptor. An attack-elastic estimator for the linear time-varying system was designed and the robustness of the estimator was analyzed as well [36]. An elastic self-adaptive filter was proposed in [37] for network attack defense and verified on a ground robot platform. It demonstrated that this algorithm could provide a better estimation results than an attack-elastic estimator.

However, the previous research on state estimation under network attack only focuses on the linear system. But the practical CPS is mostly a nonlinear system and suffers from the heavy data transmission and inadequate bandwidth. Therefore, it is necessary to investigate the issue of nonlinear state estimation when a channel is subject to network attack with the event triggered sampling strategy.

1.3 Development of the Event Triggered Filter

The concept of event triggered sampling was initially proposed by Ho et al. on the discrete event system in the early 1980s [38]. Different from traditional periodic sampling, in the event triggered sampling the sensor samples the data and transmits the data to the remote data center only when the specific condition is reached, which is called as *event*, which can effectively reduce the data transmission and the energy consumption of sensor nodes. This novel sampling mode aroused the focus from both the academia and the industry when Åström and Arzén creatively applied the event triggered sampling in a dynamic system with continuous state space [39, 40]. In [39], Åström compared the event based sampling and the stochastic system based periodic sampling and proved that the event based sampling could provide the better performances with smaller output variance at the same average sampling rate.

In [40], Arzén designed a PID controller based on the event triggered sampling and proved that the control performance would not decline when the CPU utilization ratio was substantially reduced, which promoted the continuous development of signal processing technology based on event triggered sampling. This section will summarize the research on the event triggered filtering from two perspectives: event triggered sampling strategy design and the filter design based on event triggered sampling.

1.3.1 Design of Event Triggered Sampling Strategy

In [39], Åström proved that the performance can be improved for both the continuous time system and the discrete system as long as a reasonable event triggering strategy is designed. Inspired by this, the early research primarily focused on even triggered sampling strategy design.

In general, the event triggered sampling strategy design has multiple conflict objectives. The conflicts between communication rate and filtering accuracy dominate in the design of event triggered filter. To address this problem and achieve multiple objectives, it is generally turned into the constrained optimization problem so that some objectives are listed into the objective function and others as the constraints [41–46]. Based on this, the transmission and scheduling were studied for the event based optimal finite-time sensor regarding the continuous time and discrete time scalar linear system [41, 42]. By relaxing the zero-mean initial conditions and considering the measurement noise, the previous results were further extended to a linear vector system [43]. The adaptive sampling method was developed for the continuous time linear system state estimation [46]. The relationship between sampling performance and mean sampling rate was analyzed and the suboptimal event triggered sampling strategy was further proposed, which could guarantee the minimum mean sampling rate [47].

Another method of addressing multi-objective conflicts is to include different weighted items into the objective function of the optimization [48, 49]. Following this concept, one event triggered sampling strategy was proposed to guarantee the error covariance boundedness through balancing the estimation of error covariance and communication rate [48, 49]. The distributed event triggered estimation was studied in [50] and one global event triggered communication strategy was developed for the state estimation through minimizing the weighted function of network energy consumption and communication cost and considering the estimation performance constraints. The joint design of event triggered sampling strategy and estimation was considered for the first-order stochastic system with the noise of arbitrary distribution [51], where the gaming theory framework was utilized to analyze the optimal tradeoff between mean square estimation error and the corresponding expected transmission rate.

Except the previous achievements, some researchers also proposed other methods to design an event triggered sampling strategy. For example, the periodic

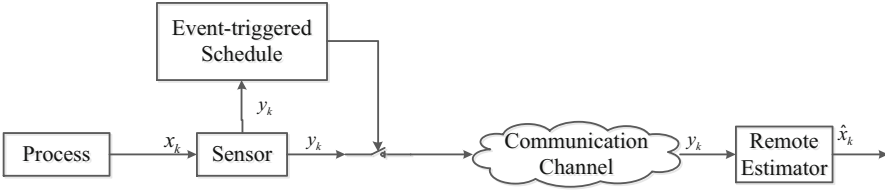


Fig. 1.6 The system diagram of event triggered dynamic state estimation. The data sampled by the sensor is determined to be sent at the node by the event triggered schedule

sampling and event triggered sampling were combined in [42] and one mixed data sampling method was further proposed to reduce the computation complexity. The previous research designed the multiple event based sampling strategies from various perspectives and thus provided an important theoretical basis for the further design of the event triggered filters.

1.3.2 Design of Event Triggered Filtering

The state estimation not only plays an important role in the design of feedback controller but also is essential to the performance monitoring and fault detection of a complicated dynamic system. Therefore, other than the research on event triggered sampling strategy design, designing the optimal filter for specific event triggered sampling strategy is also a hot topic of research.

The state estimation system based on event triggered sampling is shown in Fig. 1.6. In a state estimation system based on event triggered sampling, the measurements will be transmitted to the remote filter only when the specifically pre-designed event is satisfied although the sensor still samples the actual physical system at each sampling time. Therefore, the filter must deal with the measurement set containing “point value” and “set value” at each time instance in order to acquire the optimal estimation performance. When the remote filter receives the measurement, the filter will use the “point value” for updating. On the other hand, when the remote filter does not receive the measurement, the filter is still acquainted that the current measurement satisfies the event triggering conditions, i.e., the measurement contained in the event triggering conditions. In this case, the filter carries out the update according to the “set value” data. Based on this inspiration, many researchers have conducted the work considering different practical applications.

Based on the Gaussian hypothesis of system state condition distribution, the minimum mean square error filter was designed [52] for the innovational based event triggered sampling strategy and the analytical expression of communication rate was inferred theoretically, where the relationship between the estimation performance and communication rate was analyzed. The previous results were extended to the

event triggered sampling strategy based on sending data (Send-on-Delta) in [53]. By means of using the finite number of Gaussian distribution and approximate even distribution, the filter was proposed based on event triggered sampling strategy with a mixed updating mechanism [54]. One stochastic event triggered sampling strategy was proposed in [45] and the minimum mean square error filter was derived for the closed loop stochastic event triggered sampling strategy without introducing extra approximation. The sufficient conditions were provided in [55] for the existence of filter with expected performances regarding one certain nonlinear stochastic system with time delay. The Markov chain approximation algorithm was proposed to address the event triggered filtering of the nonlinear system [56]. Regarding the estimation of the event triggered sampling strategy of the hidden Markov model, the upgrade of system state was inferred considering the reliable channel and packet loss [57]. The performances of the linear filter were compared considering the periodic sampling and event triggered sampling and a quantitative comparison of the first-order and the second-order system was performed [58]. An event triggered sampling strategy based on state estimation of error covariance matrix was proposed and the convergence of the triggering strategy was strictly proved. It also showed that the triggering strategy can be designed offline [59].

In the previous research, the Gaussian assumption is adopted to directly address the non-Gaussian problem caused by the event triggered sampling strategy. However, many researchers also applied other methods to indirectly address this problem. The noise and event triggered sampling strategy were taken as a stochastic and non-stochastic uncertainty, respectively, and the filter based on event triggered sampling was derived by minimizing the mean square error in the worst conditions. According to this concept, the set value filtering was utilized to address the design issue of filters based on event triggered sampling [44]. In response to the event triggered sampling strategy proposed in [52], the constrained optimization was utilized to address the maximum likelihood estimation under this strategy [60]. The calculation of the upper and lower bound of the communication rate was discussed under this strategy [61]. The distributed filtering based on event triggered sampling was studied and the stability of the filter was further analyzed considering the unconditional distribution [62].

Meanwhile, there are also extensive researches on the filters for the optimal event triggered sampling regarding the different indexes, among which the robustness H_∞ based filtering method gained the greatest concern. The robustness H_∞ based filtering method was initially developed based on the gaming theory and Riccati equation for the periodically sampled linear system. With the help of linear matrix inequality (LMI) equation, it has been successfully extended to the event triggered sampling strategy [63–65]. In this method, the performance of filter based on event triggered sampling is normally quantified according to the dynamic stability of filter error and the L_2 gain between the disturbance and estimation error. Although this method can only guarantee the filtering performance in the worst condition, the joint design of the filter and the event sampling strategy was facilitated with the capability to handle the packet dropout and time delay [66, 67]. Based on such idea, on the H_∞ filtering based on event triggered sampling strategy was studied for

the communication network with delay and the sufficient condition was obtained to ensure the index stability by using the Lyapunov–Krasovskii function [68]. A general event triggering framework for the discrete time-varying system was developed, which has an attenuated communication channel, and the recursive LMI method was utilized to design the filter gain [69]. The LMI tool was developed for the H_∞ filter based on event triggered sampling [70]. The consensus filtering of distributed H_∞ based on event triggered sampling was studied and the coordinated design algorithm was proposed to obtain the filter gain and the threshold parameter of event triggered sampling strategy was acquired based on the bounded real number lemma [71].

The previous research on the event triggered filtering are all carried out for the linear system instead of the nonlinear system. Furthermore, most only provides the filter design instead of the qualitative proof of filter performance and stability [72, 73]. Because the physical models in the CPS are mostly nonlinear, it is necessary to design the nonlinear filter based on the event triggered sampling and prove its corresponding stability.

1.4 Development of Nonlinear Filtering

Generally, the high accuracy state estimation can effectively improve the accuracy and effectiveness of the control system. As an important branch of control theory, the state estimation theory has received extensive attention from academics. In the early nineteenth century, Gauss proposed the least square estimation algorithm, which is considered by academics as the earliest optimal estimation and has been applied till now. Under nonsingular situations of relevant Gramian matrix, this method only requires the least square error of the observation constraint equation and can acquire the unique solution of unknown variables but without the need for the statistic characteristics of observation. Therefore, this method can be easily realized from an engineering perspective. But the least square method suffers from the inadequate estimation accuracy [74]. In the 1940s, Wiener and Kolmogorov proposed the Wiener filtering successively applicable for the continuous time system and the discrete time system, which found the theoretical basis of estimation including forecast, filtering, and smoothing [75, 76]. The Wiener filtering fully uses the statistic characteristics of measurement and input signals. Together with the linear system theory, the optimal method was given to filter the disturbances of known statistic characteristics during the generalized stability process under the least mean square error criteria. As the Wiener filtering estimates the states at the current time instance according to all observations of the system, it is only applicable for a stable stochastic process and requires solving the Wiener–Hopf equation, which needs huge storage and high computation complexity and it is unsuitable to deal with the vector problem. Therefore, it has remarkable restrictions in application and cannot be extensively applied in practice. In 1960, in order to address the problem of high accuracy state estimation for NASA’s moon landing initiative, Kalman summarized

the concepts of minimum mean square error, probability theory and stochastic system, and introduced the state variable into Weiner filtering and further proposed the epoch-making Kalman filter for the linear time domain state space model [77]. The Kalman filtering realizes the estimation for the time-varying unstable stochastic process and multi-dimensional signal through the iteration within the time domain, beyond the constraints of Weiner filtering, making it easy implementation on a computer.

Although it was proved later that Kalman filtering was the unbiased optimal filter in the sense of both mean square error and maximum likelihood from multiple perspectives [78–80], Kalman filtering is only applicable for the linear system. However, the nonlinear system prevails in engineering. Therefore, the optimal nonlinear filter was inferred based on the previous work and the critical fundamental for the iterative computation of optimal nonlinear filter in the sense of mean square error is to solve one second-order nonlinear partial differential equation [81–83]. Since there is generally no analytical solution for the second-order nonlinear partial differential equation, and huge computation is required to derive the numerical solution, it is almost impossible to realize the iterative computation of optimal nonlinear filtering. Therefore, the researchers began to seek the design of nonlinear suboptimal filter with adequate accuracy and high filtering stability. Its design concept is to approximate the optimal nonlinear filter according to one certain approximation principles. The approximation method can be categorized into the nonlinear filtering based on Taylor expansion approximation, the filtering based on deterministic sampling and filtering based on stochastic sampling.

1.4.1 Nonlinear Filtering Based on Taylor Expansion Approximation

To address the state estimation for nonlinear system in the Apollo Program, Schmidt et al. proposed the extended Kalman filter (EKF) based on Kalman filtering [84, 85]. The EKF performs the Taylor series expansion on the nonlinear state and observation equation at the steady state, but only the first order is taken into consideration, and then the Jacobian matrix is used to replace the original nonlinear function. Based on this, the linear Kalman filtering is further used for the iterated estimation. Since this filtering algorithm is easy to be implemented using Taylor expansion, EKF has been extensively applied in engineering in the last several decades.

However, the EKF is only applicable for the nonlinear system that can be locally linearized, and the round off error is introduced during the linearization. Therefore, the accuracy of the filter will decline sharply and even become divergent when the system is of strong nonlinearity. To reduce the influence of linear round off error and increase the filtering accuracy for EKF, various EKF variants have been developed. The nonlinear filter was proposed that used the estimation results as the