A SURVEY OF STATE ESTIMATION AND APPLICATION FOR ALLOCATION LSP CAPACITY ON MPLS NETWORK

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Abstract: For most of the measuring methods of traditional control theory, measuring equipments are located at the output of the system to measure quantities transformed from non-electrical form into electrical one. This method helps us to define the value of parameters to be measured, but it has limitation because it can only assess the efficiency of a movement process. That means we can not understand the inner kinetics which is the essence of the system. In the modern control theory, states of system are considered as the feedback to the control process, which helps us to assess the elements in the inside of the system. In this paper, we survey methods for estimating states being not exposed to the correct measurements. Using this method, we also suggest an application for giving an estimate of the traffic on the LSPs to adapt the network configuration for changing traffic conditions.

Keywords: State Estimator, Observer, EKF, MPLS

I. Introduction

As widely known, states of system play a very important role in the modern control theory because they are the feedback to the control process of the plant [2]. It means that each state is available in the output of system. However, measuring states, either directly or indirectly, is often difficult because of the many various reasons [7]. Therefore, it is necessary to estimate states of system so that we can use them for the control process, the measurement of network's parameters as well as for the purpose of assessing technologies [3]. One solution for state estimation is to introduce additional process knowledge in the form of a model and constraints. The goal of state estimation is to reconstruct the state of a system from process measurements and a model.

In this article, besides putting forward the matter and going to the conclusion in opening way in section VI, the article will concentrate on four main matters. In section II, we present the role of estimator as the feedback in the modern control theory [2], [4]. State estimation for linear time invariable dynamical system without disturbance is presented in section III [1], [2], [12], in which we introduce ideal assumption for easier survey and estimation. It has significance in theory more than practical problem. Furthermore, state estimation for dynamical system which addresses many different challenges, including nonlinear dynamics, states subject to hard constraints, disturbance and local optimal is presented in section IV [7]. In which, we will introduce state estimator based on the extended Kalman filter theory. Finally, in section V, we present the application of state estimation for giving an estimate of the traffic on the LSPs currently on MPLS network [10],[11].

II. Role of the Estimator

First of all, we should judge that for control problem, both traditional and modern control methods use the feedback model. The signal used feedback in traditional process is output signal and itself appeared derivative (Figure 2.1) while for the theory of modern control, states are used as the feedback for control system (Figure 2.2).

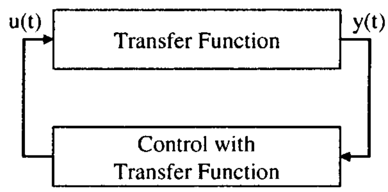

Figure 2.1. Feedback in Traditional Control

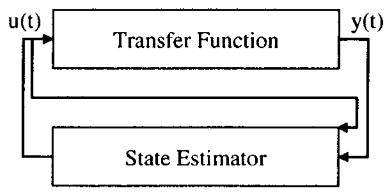

Figure 2.2. Feedback in Modern Control

In implementing this method, people often think that states of system are available and measurable signals. However, measuring the state, either directly or indirectly is often difficult. Because of this, it is necessary to estimate states of system so that we can use them for the control process: the measurement of network's parameters as well as for the purpose of assessing technologies. It means that we should design a state estimator in the output of system for control process.

Roughly, the goal of state estimation is to reconstruct the state of a system from process measurements and a model. For evident understanding, we will consider the system consisting of relative problem as regulator, process, estimator and target calculation in the following figure (Figure 2.3).

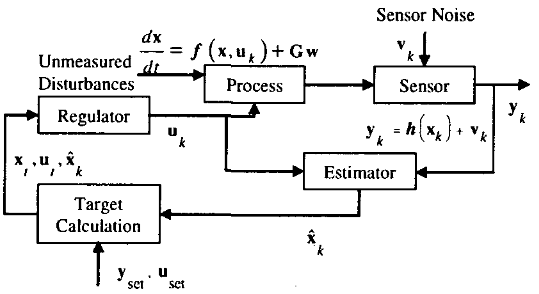

Figure 2.3. Role of estimator in control process

III. State estimation for linear time-invariable dynamical system

We will consider the n- dimensional linear time-invariable dynamical equation:

FE: $$\dot{\mathbf{x}} = \mathbf{Ax} + \mathbf{Bu} \quad (3.1)$$
$$\mathbf{y} = \mathbf{Cx} \quad (3.2)$$

in which: **A, B, C** are real constant matrices with alternate dimension *nxn, nxp, qxn.*

It is assumed that state variables are not accessible and the matrices **A, B, C** are completely known. Hence the problem is to estimate or to generate **x**(t) from the available input **u**(t) and output **y**(t) with the knowledge of the matrices **A, B** and **C**. If we know matrices **A** and **B**, we can duplicate the original system as shown in Figure 3.1. We called the system an *open-loop estimator.*

From Figure 3.1, we can easily identify that only the input is used for estimation in case of an open-loop estimator. It is conceivable that if both the output and input are utilized, the performance of an estimator can be improved. Based on this idea, we can design a state estimator as Figure 3.2. This estimator will be called an *asymptotic state estimator.*

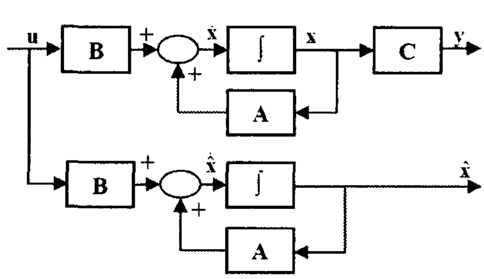

Figure 3.1. Open-loop Estimator

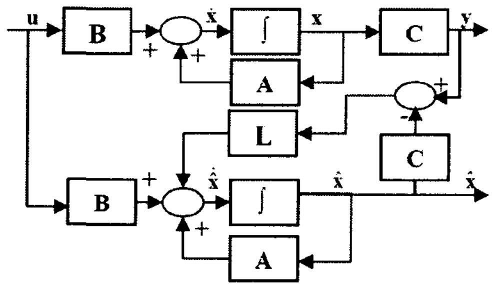

Figure 3.2. An Asymptotic State Estimator

The dynamical equation of asymptotic state estimator shown in Figure 3.2 is given by:

$$\dot{\hat{\mathbf{x}}} = \mathbf{A}\hat{\mathbf{x}} + \mathbf{Bu} + \mathbf{L}(\mathbf{y} - \mathbf{C}\hat{\mathbf{x}}) \quad (3.3)$$

which can be written as:

$$\dot{\hat{\mathbf{x}}} = (\mathbf{A} - \mathbf{LC})\hat{\mathbf{x}} + \mathbf{Bu} + \mathbf{Ly} \quad (3.4)$$

Above we have presented the basic theory of asymptotic state estimator. In the following section, a design algorithm will be mentioned.

Consider the n-dimensional dynamical equation:

FE: $$\dot{\mathbf{x}} = \mathbf{Ax} + \mathbf{Bu} \quad (3.5)$$
$$\mathbf{y} = \mathbf{Cx} \quad (3.6)$$

where **A, B,** and **C** are, respectively, *nxn, nxp, qxn* real constant matrices . It is assumed that FE is irreducible. We define the n-dimensional dynamical equation:

$$\dot{\mathbf{z}} = \mathbf{Fz} + \mathbf{Gy} + \mathbf{Hu} \quad (3.7)$$

where **F, G, H** are, respectively, *nxn, nxq,*and *nxp* real constant matrices.

We can express a following theorem [2]: The state **z**(t) in equation (3.7) is an estimation of **Tx**(t) for some *nxn* real constant matrix **T** in the sense that **z**(t)-**Tx**(t) → 0 with any **x**(0), **z**(0) and **u**(t) if and only iff :

1. **TA - FT = GC**;
2. **H = TB**; (3.8)
3. All eigenvalues of **F** have negative real parts.

Based on this theorem, we show **z**(t) is estimation of **Tx**(t). So we can now propose a design algorithm:

1. Choose an **F** so that all of its eigenvalues have negative real parts and are disjoint from those of A;
2. Choose a **G** so that {**F, G**} being controllable;
3. Solve the unique **T** in **TA-FT=GC**;
4. If **T** is nonsingular, compute **H=TB**. The equation (3.7) with **F, G**, and **H** is an estimate of **Tx**(t) or $\hat{\mathbf{x}}(t) = \mathbf{T}^{-1}\mathbf{z}(t)$. If **T** is singular, choose different **F** and/or **G**, and repeat the process.

IV. A Critical Evaluation of Extended Kalman Filtering

1. Formulation of the Estimation Problem

In modern telecommunications engineering systems, most processes consist of continuous processes with discrete measurements. In general, one derives a first principles model by assuming that the continuous process is deterministic, and then one uses Bayesian estimation to estimate the model parameters from process measurements. This model is equivalent to:

$$\mathbf{x}_{k+1} = \overline{F}\left(\mathbf{x}_k, u_k, \theta\right) \qquad (4.1a)$$
$$\mathbf{y}_k = \mathbf{h}\left(\mathbf{x}_k\right) + \mathbf{v}_k \qquad (4.1b)$$

in which $\mathbf{v}_k$ is a N(0, R_k) noise which denotes a normal distribution with mean 0 and covariance R_k.

In contrast to equation (4.1), many recent models permit random disturbances to affect the model propagation step. Parameter estimation for nonlinear variations of such models is a subject of on-going research. For this work, we choose the discrete stochastic system model:

$$\mathbf{x}_{k+1} = \mathbf{F}\left(\mathbf{x}_k, \mathbf{u}_k\right) + \mathbf{G}\left(\mathbf{x}_k, \mathbf{u}_k\right)\mathbf{w}_k \qquad (4.2a)$$
$$\mathbf{y}_k = \mathbf{h}\left(\mathbf{x}_k\right) + \mathbf{v}_k \qquad (4.2b)$$

in which $\mathbf{W}_k$ is a N(0, Q_k) noise.

Ideally, state estimators should solve the problem:

$$\hat{\mathbf{x}}_T = \arg\max_{x_T} \mathbf{p}\left(\mathbf{x}_T \middle| \mathbf{y}_0, \ldots, \mathbf{y}_T\right) \qquad (4.3)$$

in which $\mathbf{p}\left(\mathbf{x}_T \middle| \mathbf{y}_0, \ldots, \mathbf{y}_T\right)$ is the probability that the state of the system is x_T under given measurements $\mathbf{y}_0, \cdots, \mathbf{y}_T$. Equation (4.3) is referred to as the maximum likelihood estimate. In the special case that the system is not constrained and in equation (4.2) satisfying:

1. $\mathbf{F}\left(\mathbf{x}_k, \mathbf{u}_k\right)$ is linear with respect to $\mathbf{x}_k$,
2. $\mathbf{h}\left(\mathbf{x}_k\right)$ is linear with respect to $\mathbf{x}_k$, and
3. $\mathbf{G}\left(\mathbf{x}_k, \mathbf{u}_k\right)$ is a constant matrix.

The maximum likelihood estimator is the Kalman filter.

2. Extended Kalman Filtering (EKF)

The extended Kalman filter is one approximation for calculating equation (4.3). The EKF linearizes nonlinear systems, and applies the Kalman filter (the optimal, unconstrained, linear state estimator) to obtain the state estimates. The tacit approximation here is that the process statistics are multivariate normal distributions. We summarize the algorithm for implementing the EKF presented by Stengel [8].

The assumed prior knowledge is identical to that of the Kalman filter:

$$\overline{\mathbf{x}}_0 \text{ given} \qquad (4.4a)$$
$$p_0 = \mathbf{E}\left[\left(\mathbf{x} - \overline{\mathbf{x}}_0\right)\left(\mathbf{x} - \overline{\mathbf{x}}_0\right)^T\right] \qquad (4.4b)$$
$$\mathbf{R}_k = \mathbf{E}\left[\mathbf{v}_k \mathbf{v}_k^T\right] \qquad (4.4c)$$
$$\mathbf{Q}_k = \mathbf{E}\left[\mathbf{w}_k \mathbf{w}_k^T\right] \qquad (4.4d)$$

The approximation uses the following linearized portions of equation (4.2) to implement the following algorithm:

$$\mathbf{A}_k = \left.\frac{\partial \mathbf{F}(\mathbf{x},\mathbf{u})}{\partial \mathbf{x}^T}\right|_{x=\hat{x}_k, u=u_k} \quad (4.5), \qquad \mathbf{C}_k = \left.\frac{\partial \mathbf{h}(\mathbf{x})}{\partial \mathbf{x}^T}\right|_{x=\hat{x}_k} \quad (4.6)$$

1. At each measurement time, compute the filter gain **L** and update the state estimate and covariance matrix:

$$\mathbf{L}_k = \mathbf{P}_{k|k-1}\mathbf{C}_k^T\left[\mathbf{C}_k\mathbf{P}_{k|k-1}\mathbf{C}_k^T + \mathbf{R}_k\right]^{-1} \qquad (4.7)$$
$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{L}_k\left(\mathbf{y}_k - \mathbf{h}\left(\hat{\mathbf{x}}_{k|k-1}\right)\right) \qquad (4.8)$$

$$\mathbf{P}_{k|k} = \mathbf{P}_{k|k-1} - \mathbf{L}_k \mathbf{C}_k \mathbf{P}_{k|k-1} \quad (4.9)$$

2. Propagate the state estimate and covariance matrix to the next measurement time via the equations:

$$\hat{\mathbf{x}}_{k+1|k} = \mathbf{F}\left(\hat{\mathbf{x}}_k, \mathbf{u}_k\right) \quad (4.10)$$

$$\mathbf{P}_{k+1|k} = \mathbf{A}_k \mathbf{P}_{k|k} \mathbf{A}_k^T + \mathbf{G}_k \mathbf{Q}_k \mathbf{G}_k^T \quad (4.11)$$

3. Let $k \leftarrow k + 1$. Return to step 1.

V. Application on Kalman Filter Estimation Based LSP Capacity Allocation

Figure 5.1 show the role of state estimation on TE problem having relative to planning process in MPLS Networks. The following scheme performs an optimal estimate of the amount of traffic utilizing the LSP based on a measurement of the instantaneous traffic load. This estimate is used to forecast the traffic bandwidth requests so that resources can be provisioned on the LSP to satisfy the QoS of the requests. The estimation is performed by the use of Kalman filter theory as section IV while the forecast procedure is based on deriving the transient probabilities of the possible system states.

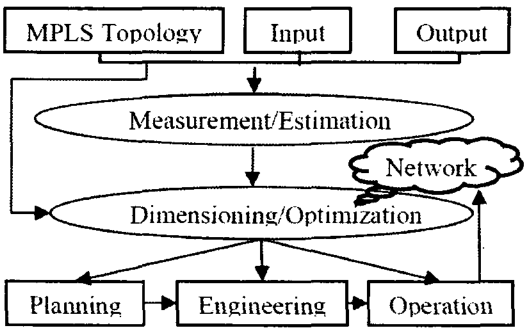

Figure 5.1. Planning Process in MPLS

There exists an LSP (i,j) between two routers in MPLS Network. We estimate the level of traffic on this LSP, for a given traffic class, based on a periodic measurement of the aggregate traffic on LSP (i,j). We assume that the traffic measurements are performed at discrete time-points mT (m= 1, 2, …, M) for a given value of T. At the time instant m (corresponding to mT), the aggregate traffic on the LSP for a given traffic class is denoted by $\mathbf{y}$(m). We also assume that for the duration (0, MT], the number of established sessions that use the LSP is N. For each session, flows are defined as the active periods. So, each session has a sequence of flows separated by periods of inactivity. For a given traffic class, we denote by $\mathbf{x}$(m) the number of flows at the instant m and by $\mathbf{x}(mT+t)$, $t \in (0, T]$ the number of flows in the time interval $(mT, (m+1)T]$, without notational conflict. Clearly, $\mathbf{x}(m) \leq N$ and is not known or measurable. We assume that each flow within the traffic class has a constant rate of b bits per second. So, nominally, for a traffic class:

$$\mathbf{y}(m) = \mathbf{b}\mathbf{x}(m) \quad (5.1)$$

The only measurable variable in the system is $\bar{\mathbf{y}}(m)$, which is a measure, corrupted by noise of the aggregate traffic on the LSP. Nominally, $\mathbf{x}(m) = \mathbf{y}(m) / \mathbf{b}$, but we do not have access to the correct measurements of $\mathbf{y}(m)$, even though b is a known quantity for a particular traffic class. Thus, we propose to use the Kalman filter setup to evaluate $\hat{\mathbf{x}}(m)$, an estimate of the actual $\mathbf{x}(m)$, using $\bar{\mathbf{y}}(m)$ the noisy measurements. To this purpose, we define $\mathbf{p}_k(t)$, $t \in (mT, (m+1)T]$ to be the probability that the number of active flows at time t is k, i.e., for $t \in (mT, (m+1)T]$:

$$\mathbf{p}_k(t) \overset{\Delta}{=} prob\{\mathbf{x}(t) = k\} \quad (5.2)$$

The state transition rate diagram is shown in following Figure 5.2. The diagram depicts transitions among the states. The above model for the flows is assumed to be Poisson with exponentially distributed interarrival times (parameter λ) and durations (parameter μ).

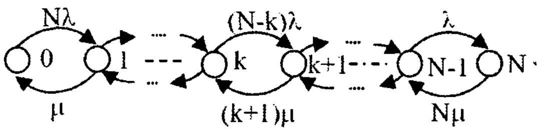

Figure 5.2. State Transition Rate

From the diagram and by using queuing theory [9], we can write the following differential equations (5.3)-(5.5) for the probabilities $\mathbf{p}_k$(t)

$$\frac{d\mathbf{p}_0(t)}{dt} = \mu\mathbf{p}_1(t) - N\lambda\mathbf{p}_0(t) \quad (5.3)$$

$$\frac{d\mathbf{p}_k(t)}{dt} = (N-k+1)\lambda\mathbf{p}_{k-1}(t) + (k+1)\mu\mathbf{p}_{k+1}(t)$$
$$-\{k\mu + (N-k)\lambda\}\mathbf{p}_k(t), 1 \le k < N \quad (5.4)$$

$$\frac{d\mathbf{p}_N(t)}{dt} = \lambda\mathbf{p}_{N-1}(t) - N\mu\mathbf{p}_N(t) \quad (5.5)$$

The generating function **G**(z, t)is defined as the z-transform of the probability distribution function. We calculate ∂ **G**(z, t) / ∂ t using (5.3)-(5.5) as:

$$\mathbf{G}(z,t) \overset{\Delta}{=} \sum_{j=0}^{N} \mathbf{p}_j(t) z^j \quad (5.6)$$

$$\frac{\partial \mathbf{G}(z,t)}{\partial t} = \mathbf{G}(z,t)N\lambda(z-1) - \frac{\partial \mathbf{G}(z,t)}{\partial z}(z-1)(\lambda z + \mu) \quad (5.7)$$

Utilizing the initial condition **G**(z, mT) = $\mathbf{z}^{\mathbf{x}(m)}$, i.e., the number of active flows at time mT is **x**(m), we arrive at the following solution for **G**(z, t) for t $\in$ (mT, (m+1)T]:

$$\mathbf{G}(z,t) = \mathbf{C}(z,t)^{\mathbf{x}(m)} \left(\frac{\lambda z + \mu}{\lambda \mathbf{C}(z,t) + \mu} \right)^N \quad (5.8)$$

where:

$$\mathbf{C}(z,t) = \frac{\lambda z + \mu - \mu(z-1)e^{-t(\lambda+\mu)}}{\lambda z + \mu - \lambda(z-1)e^{-t(\lambda+\mu)}} \quad (5.9)$$

By the definition of the generating function and the special properties of the z-transform, we get:

$$\mathbf{E}\left[\mathbf{x}(m+1) \middle| \mathbf{x}(m)\right] = \left.\frac{\partial \mathbf{G}(z,T)}{\partial z}\right|_{z=1}$$
$$= \mathbf{x}(m)e^{-T(\lambda+\mu)} + \frac{N\lambda}{\lambda+\mu}\left(1 - e^{-T(\lambda+\mu)}\right) \quad (5.10)$$

Thus, from the Kalman filter setup, we get:

$$\hat{\mathbf{x}}(m) = \mathbf{A}\hat{\mathbf{x}}(m-1) + \mathbf{B}$$
$$+\mathbf{k}(m)\left[\bar{\mathbf{y}}(m) - \mathbf{CA}\hat{\mathbf{x}}(m-1) - \mathbf{CB}\right] \quad (5.11)$$

where **k**(m) is Kalman filter gain and:

$$\mathbf{A} = e^{-T(\lambda+\mu)}; \quad \mathbf{B} = \frac{N\lambda}{\lambda+\mu}\left[1 - e^{-T(\lambda+\mu)}\right]$$
$$\mathbf{C} = \mathrm{b}$$

This gives an estimate of the traffic on the LSP currently. This estimate will be used to forecast the traffic for the purpose of resource reservation.

VI. Conclusion

In this paper, we have presented the role of state signals in the modem control theory and introduced the basic methods of state estimation. Depending on definite dynamic model (linear, nonlinear, disturbance, without disturbance, etc.), we can apply suitable methods. Many contents of this paper concentrate on state estimation based on the Kalman filter theory as well as its extension. It is well established that the Kalman filter is the optimal state estimator for unconstrained, linear systems subject to normally distributed state and noise in measurement. However, many physical systems exhibit nonlinear dynamics and have states subject to hard constraints. Hence, Kalman filtering is no longer directly applicable. As a result, many different types of nonlinear state estimators have been proposed, such as extended Kalman filters, moving horizon estimation, model inversion, and Bayesian estimation. In this paper, we only present the outline of state estimation for linear invariable dynamic system without disturbance and extended Kalman filters. Other types of nonlinear state estimators and their application will be researched in the future.

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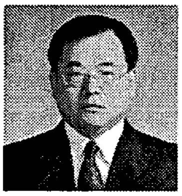

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