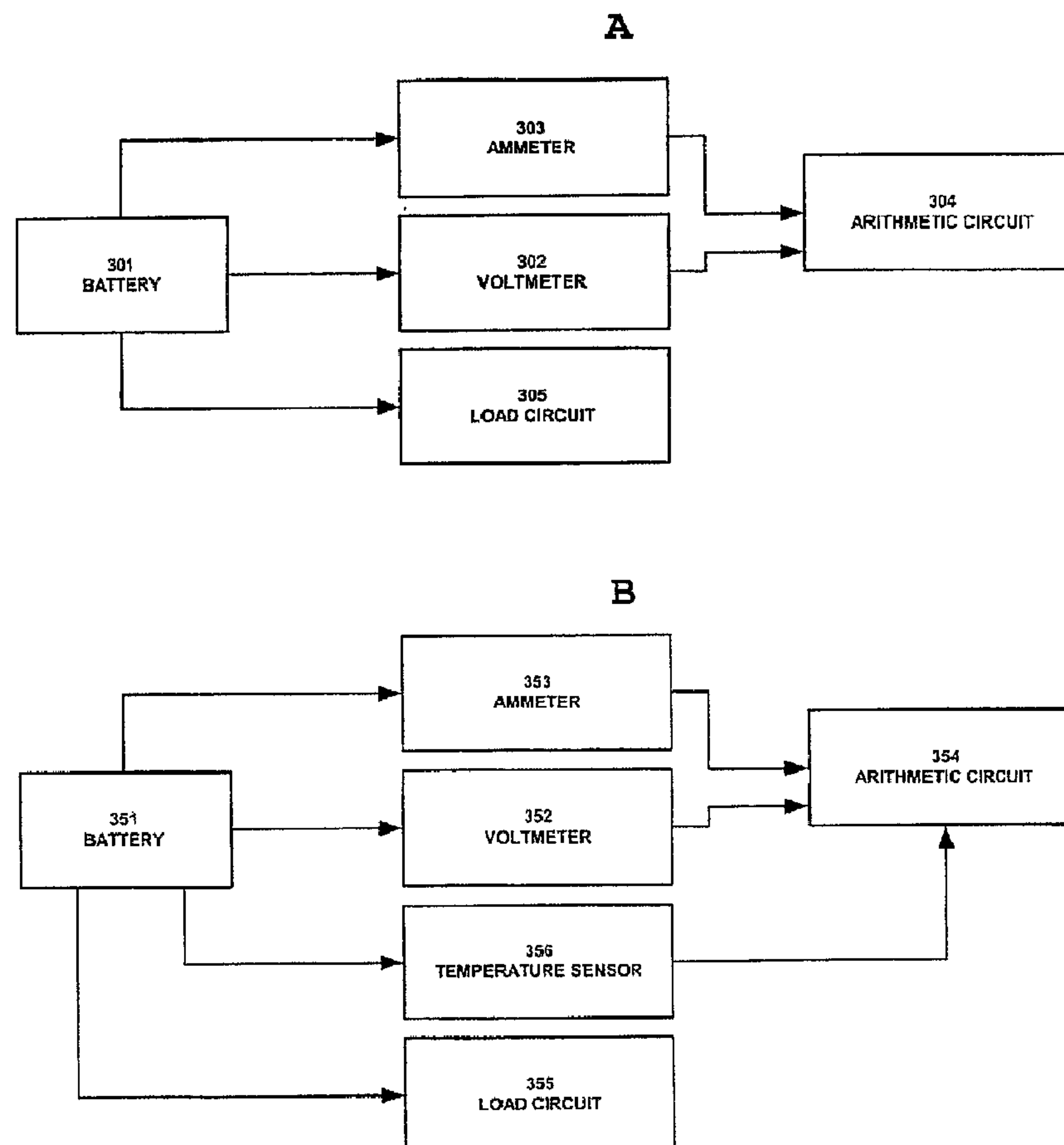




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(54) Titre : PROCEDE ET SYSTEME D'ESTIMATION DE PARAMETRES ET D'ETATS D'UNE BATTERIE
(54) Title: METHOD AND SYSTEM FOR BATTERY STATE AND PARAMETER ESTIMATION



(57) Abrégé/Abstract:

Methods and systems for estimating values descriptive of a battery's present operating condition, comprising: estimating state-of-charge in a battery where said state-of-charge is comprised one of the internal states; and estimating state-of-health in a battery



(57) Abrégé(suite)/Abstract(continued):

where said state-of-health is comprised one of the internal parameters. In particular, methods for estimating state-of-charge in a battery, comprising: making an internal states prediction of said battery where said state-of-charge is one of said internal states; making an uncertainty prediction of said internal states prediction; correcting said internal states prediction and said uncertainty prediction; and applying an algorithm that iterates said making an internal states prediction, said making an uncertainty prediction and said correcting to yield an ongoing estimation to said state-of-charge and an ongoing uncertainty to said state-of-charge estimation. And methods and systems for estimating present parameters of an electrochemical cell system comprising: making an internal parameter prediction of the cell; making an uncertainty prediction of the internal parameter prediction; correcting the internal parameter prediction and the uncertainty prediction; and applying an algorithm that iterates the internal parameter prediction, and the uncertainty prediction and the correction to yield an ongoing estimation to the parameters and an ongoing uncertainty to the parameters estimation.

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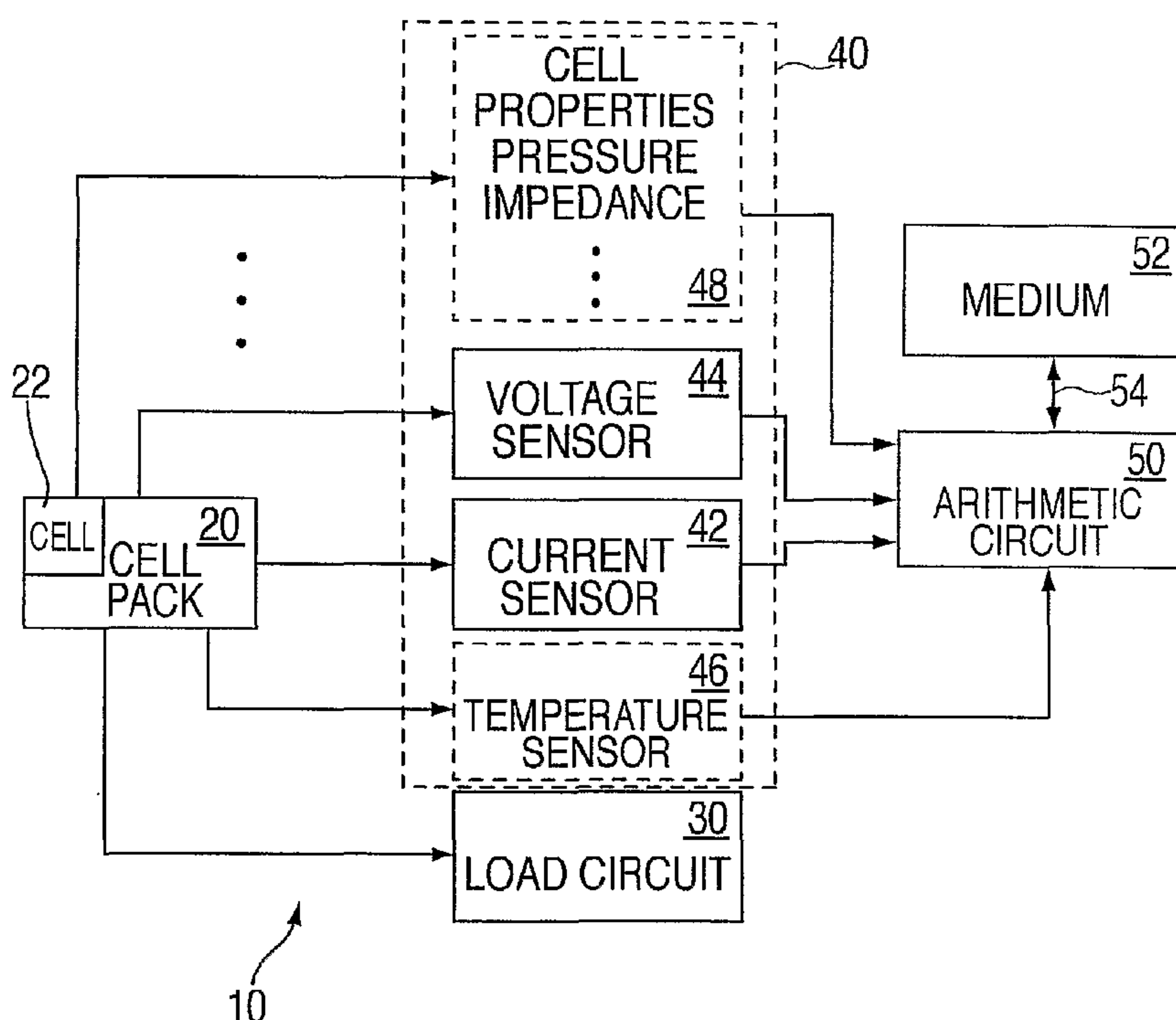
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(54) Title: METHOD AND SYSTEM FOR BATTERY STATE AND PARAMETER ESTIMATION



(57) Abstract: Methods and systems for estimating values descriptive of a battery's present operating condition, comprising: estimating state-of-charge in a battery where said state-of-charge is comprised one of the internal states; and estimating state-of-health in a battery where said state-of-health is comprised one of the internal parameters. In particular, methods for estimating state-of-charge in a battery, comprising: making an internal states prediction of said battery where said state-of-charge is one of said internal states; making an uncertainty prediction of said internal states prediction; correcting said internal states prediction and said uncertainty prediction; and applying an algorithm that iterates said making an internal states prediction, said making an uncertainty prediction and said correcting to yield an ongoing estimation to said state-of-charge and an ongoing uncertainty to

said state-of-charge estimation. And methods and systems for estimating present parameters of an electrochemical cell system comprising: making an internal parameter prediction of the cell; making an uncertainty prediction of the internal parameter prediction; correcting the internal parameter prediction and the uncertainty prediction; and applying an algorithm that iterates the internal parameter prediction, and the uncertainty prediction and the correction to yield an ongoing estimation to the parameters and an ongoing uncertainty to the parameters estimation.

WO 2006/057468 A1

WO 2006/057468 A1



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METHOD AND SYSTEM FOR BATTERY STATE AND PARAMETER ESTIMATION**Technical Field**

The present invention relates to methods and apparatus
5 for estimation of battery pack system states and parameters
using digital filtering techniques. In particular, Kalman
filtering and extended Kalman filtering. Battery management
systems in battery packs must estimate values descriptive of
the pack's present operating condition, which include battery
10 state-of-charge (SOC) and power-fade, capacity-fade, and
instantaneous available power. The power-fade and capacity-
fade are often lumped under the description state-of-health
(SOH). The present invention provides an advanced methods
and apparatus for estimating values descriptive of the pack's
15 present operating condition including battery SOC and SOH. .

Background Art

Batteries are used in a wide variety of electronic and
electrical devices. In each application, it is often useful
20 and necessary to measure how much charge is left in the
battery. Such a measurement is called the state-of-charge
(SOC). It is useful, for example, for a cell phone user to
know how much longer he can talk on his phone. On the other
hand, recharging devices need to know how much charge is in a
25 battery to prevent overcharging. Many types of battery are
sensitive to overcharging as well as undercharging.
Overcharging and undercharging can erode the effectiveness of
batteries and even damage them.

Currently there are many techniques that measure the
30 remaining charge of a battery. Each of these SOC

determination techniques has drawbacks. Some such as Ampere-hour counting are sensitive to measurement errors. Others such as Coup de fouet work for only One type of battery. Still other techniques such as Impedance Spectroscopy are
5 constrained by battery conditions such as rapidly changing temperature. Also many do not give an uncertainty range in their estimation of the SOC. In applications such as HEV and EV batteries, the uncertainty range associated with the SOC measurement is very critical. Vehicles can lose power on the
10 road and cause danger if the uncertainty range is unknown and the battery is erroneously undercharged. Knowing the uncertainty range can prevent this. For example if the battery SOC is determined to be within 10% of the minimum charge threshold and the uncertainty range is known to be 15%,
15 the system will know to charge the battery because the uncertainty range is greater than the distance to the threshold.

Existing Techniques

Presented here is an overview of the existing techniques
20 and some of their shortcomings. One technique called the discharge test is an accurate form of testing. It involves completely discharging the battery to determine the SOC under controlled conditions. However, the complete discharge requirement renders this test impractical for real-life
25 application. It is too time consuming to be useful and interrupts system function while the test is being performed.

Another SOC determination technique is called Ampere-hour counting. This is the most common technique for determining the SOC because of its ease of implementation. It
30 measures the current of the battery and uses the measurement

to determine what the SOC is. Ampere-hour counting uses the following:

$$SOC = SOC_0 + \frac{1}{C_N} \int_0^t (I_{batt} - I_{loss}) dt \quad (1)$$

where C_N is the rated capacity of the battery, I_{batt} is
 5 the battery current, and I_{loss} is the current consumed by the
 loss reactions. The equation determines the SOC based on an
 initial SOC_0 starting point. Ampere-hour counting is
 essentially an "open loop" method that is easily confused.
 Measurement error accumulates over time to degrade the
 10 accuracy of SOC determination. There are methods to improve
 current measurement but they are expensive.

Electrolyte Measurement is another common technique. In
 lead-acid batteries, for example, the electrolyte takes part
 in reactions during charge and discharge. Thus, a linear
 15 relationship exists between the change in acid density and
 the SOC. Therefore measuring the electrolyte density can
 yield an estimation of the SOC. The density is measured
 directly or indirectly by ion-concentration, conductivity,
 refractive index, viscosity, etc. However, this technique is
 20 only feasible for vented lead-acid batteries. Furthermore it
 is susceptible to acid stratification in the battery, water
 loss and long term instability of the sensors.

An open-circuit voltage measurement may be performed to
 test the SOC of the battery. Although the relationship
 25 between the open circuit voltage and the SOC is non-linear,
 it may be determined via lab testing. Once the relationship
 is determined, the SOC can be determined by measuring the
 open circuit voltage. However the measurement and estimation

are accurate only when the battery is at a steady state, which can be achieved only after a long period of inactivity. This makes the open-circuit voltage technique impractical for dynamic real time application.

5 Impedance Spectroscopy is another technique used to determine the SOC. Impedance spectroscopy has a wide variety of applications in determining the various characteristics of batteries. Impedance Spectroscopy exploits a relationship between battery model parameters derived from impedance
10 spectroscopy measurements and the SOC. However the drawback of this technique is that impedance curves are strongly influenced by temperature effects. Thus its application is limited to applications where temperature is stable.

Internal resistance is a technique related to impedance
15 spectroscopy. Internal resistance is calculated as the voltage drop divided by the current change during the same time interval. The time interval chosen is critical because any time interval longer than 10 ms will result in a more complex resistance measurement. Measurement of internal
20 resistance is very sensitive to measurement accuracy. This requirement is especially difficult to achieve in Hybrid Electric Vehicle (HEV) and Electric Vehicle (EV) applications.

Some techniques use non-linear modeling to estimate SOC directly from measurements. An example is artificial neural
25 networks. Artificial neural networks operate on any system and predict the relationship between input and output. The networks have to be trained repeatedly so that it can improve its estimation. Because the accuracy of the data is based on the training program for the networks, it is difficult to

determine the error associated with the SOC prediction given by artificial neural networks.

There is another group of SOC estimation techniques called the interpretive techniques. Interpretive techniques do not give SOC directly. Instead they use electrical discharge and charge characteristics to determine the SOC. As such, the SOC must be inferred from the calculated values. One of these techniques is called the Coup de fouet. Coup de fouet describes the short voltage drop region occurring at the beginning of discharge following a full charge of lead-acid battery. Using a special correlation between the voltage parameters occurring in this Coup de fouet region, the SOC can be inferred. One limitation of the Coup de fouet technique is that it works for lead-acid batteries only. Moreover it is effective only in cases where full charge is frequently reached during battery operations.

The Kalman Filter

One SOC determination technique involves mathematically modeling the behavior of the battery and predicting the SOC based on the model. One such model is the Kalman filter. It has mathematical basis in statistics, probabilities and system modeling. The main purpose of the Kalman filter is to predict recursively the internal states of a dynamic system using only the system's outputs. In many instances this is very useful because the internal states of the system are unknown or cannot be directly measured. As such, the Kalman filter can work on all types of batteries and addresses a limitation of many aforementioned techniques.

The Kalman filter has been widely used in fields such as aerospace and computer graphics because it has several

advantages over many other similar mathematical system models. In particular, the Kalman filter takes into account both measurement uncertainty and estimation uncertainty when it updates its estimation in successive steps. The Kalman filter
5 corrects both uncertainties based on new measurements received from sensors. This is very important for two reasons. First, sensors often have a noise factor, or uncertainty, associated with its measurement. Over time, if uncorrected, the measurement uncertainty can accumulate. Second, in any
10 modeling system the estimation itself has inherent uncertainty because the internal dynamic of the system may change over time. The estimation of one time step may be less accurate than the next because the system may have changed internally to behave less similarly to the model. The
15 correction mechanism in the Kalman filter minimizes these uncertainties at each time step and prevents them from degrading accuracy over time.

FIG. 1. shows the basic operation of the Kalman filter. There are two main components in the Kalman filter-predict
20 component 101 and correct component 102. To start, a set of initial parameters are fed into predict component 101. Predict component 101 predicts the internal states of the system at a particular point in time using a set of input parameters. Besides predicting the internal states, it also
25 gives the uncertainty of its prediction. Thus, as shown in FIG. 1, the two outputs of predict component 101 are the predicted internal state vector (which encompasses the internal states) and its uncertainty.

The role of correct component 102 is to correct the
30 predicted internal states and uncertainty it receives from

predict component 101. The correction is made by comparing the predicted internal states and predicted uncertainty with new measurements received from sensors. The result are the corrected internal states and corrected uncertainty, both of which are then fed back as parameters to predict component 101 for the next iteration. At the next iteration, the cycle repeats itself over again.

Mathematical Basis of Kalman Filter

FIG. 1A and FIG. 1B show the equations used within both predict and correct components of the Kalman Filter. To understanding the origin of equations used, consider a dynamic process described by an n-th order difference equation of the form

$$y_{k+1} = a_{0,k}y_k + \dots + a_{n-1,k}y_{k-n+1} + u_k, \quad k \geq 0, \quad (2)$$

where u_k is a zero-mean white random process noise. Under some basic conditions, this difference equation can be re-written as

$$\vec{x}_{k+1} \equiv \begin{bmatrix} y_{k+1} \\ y_k \\ y_{k-1} \\ \vdots \\ y_{k-n+2} \end{bmatrix} = \underbrace{\begin{bmatrix} a_{0,k} & a_{1,k} & \cdots & a_{n-2,k} & a_{n-1,k} \\ 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{bmatrix}}_A \underbrace{\begin{bmatrix} y_k \\ y_{k-1} \\ y_{k-2} \\ \vdots \\ y_{k-n+1} \end{bmatrix}}_{\vec{x}_k} + \underbrace{\begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}}_B u_k \quad (3)$$

in which $\vec{x}_{k+1}$ represents a new state modeled by a linear combination of the previous state $\vec{x}_k$ and input u_k . Note the notation of matrices A and B. This leads to the state-space model

$$\vec{x}_{k+1} = A_k \vec{x}_k + B_k u_k \quad (4)$$

$$\vec{y}_i = [1 \ 0 \ \dots \ 0] \vec{x}_i \quad (5)$$

or the more general form

$$\vec{x}_{k+1} = A_k \vec{x}_k + B_k u_k \quad (6)$$

$$\vec{y}_k = C_k \vec{x}_k + D_k u_k \quad (7)$$

5 which is the basis of many linear estimation models. While equations (3) to (5) assume a system with a single input and a single output, the general form in equations (6), (7) and the following equations allow multiple inputs and outputs if B has multiple columns and C has multiple rows.

10 Building on equations (6) and (7), the Kalman filter is governed by the equations

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1} \quad (8)$$

$$y_k = Cx_k + Du_k + v_k. \quad (9)$$

Equation (9) is in a more general form, though D is often assumed to be 0. The matrices A and B in equation (8) relate to matrices A_k and B_k in equation (6), respectively. The matrices C and D in equation (9) relate to matrices C_k and D_k in equation (7). As equation (8) governs the estimation of the dynamic system process, it is called the process function. Similarly since equation (9) governs the estimation of the measurement uncertainty, it is called the measurement function. The added random variables w_k and v_k in equation (8) and (9) represent the process noise and measurement noise, respectively. Their contribution to the estimation is represented by their covariance matrices Σ_w and Σ_v in FIGS. 1A and 1B.

15
20
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Referring again to FIG. 1A (which shows equations in predict component 101), equation 151 is based on equation (8) and equation 152 is based on in part on equation (9). Equation 151 takes closely after the form of equation (8) but the necessary steps to transform equation (9) into the form shown in equation 152 are not shown here. Equation 151 predicts the internal states of the system in the next time step, represented vector by $\hat{x}_{k+1}(-)$, using parameters from the current time step. The minus notation denotes that the vector is the result of the predict component. The plus notation denotes that the vector is the result of the correct component. Hence in equation 151, the result of the correct component in the current time step is used to predict the result for the next time step. Equation 152 predicts the uncertainty, which is also referred to as the error covariance. As such, the matrix Σ_w in equation 152 is the process noise covariance matrix.

FIG. 1B shows the equations within correct component 102. These three equations are executed in sequence. First, equation 161 determines the Kalman Gain factor. The Kalman Gain factor is used to calibrate the correction in equations 162 and 163. The matrix C in equation 161 is from that of equation (9), which relates the state to the measurement y_k . In equation 162, the Kalman Gain factor is used to weight between actual measurement y_k and predicted measurement $C\hat{x}_k(-)$. As shown in equation 161, matrix Σ_v , the actual measurement-noise covariance, is inversely proportional to the Kalman Gain factor L_k . As Σ_v decreases, L_k increases and gives the actual measurement y_k more weight. However, if matrix $\Sigma_{e,k}(+)$, the predicted uncertainty, decreases, L_k decreases and gives

more weight to predicted measurement $C\hat{x}_k(-)$. Thus Kalman Gain factor favors either the actual measurement or predicted measurement, depending on which type of measurement has a smaller uncertainty.

5 Using this method of weighing measurement, equation 162 computes the corrected internal state vector $\hat{x}_k(+)$ based on predicted internal state vector $\hat{x}_k(-)$ (from predict component 101), new measurement y_k and predicted measurement $C\hat{x}_k(-)$. Finally in the last equation of correct component 102,
10 equation 163 corrects the predicted uncertainty, or the state-error covariance. Matrix I in equation 163 represents the identity matrix. The output of equations 162 and 163 are fed to predict component 101 for the next iteration. More specifically, the calculated value $\hat{x}_k(+)$ in equation 162 is
15 substituted into equation 151 for the next iteration and the calculated value $\Sigma_{e,k}(+)$ in equation 163 is substituted into equation 152 for the next iteration. The Kalman filter thus iteratively predicts and corrects the internal states and its associated uncertainty. It must be noted that in practice,
20 both A, B, C, D, Σ_w and Σ_v might change in each time step.

Extended Kalman Filter

Whereas the Kalman filter uses linear functions in its model, the Extended Kalman filter was developed to model system with non-linear functions. Aside from this distinction,
25 the mathematical basis and operation for the Extended Kalman filter are essentially the same as the Kalman filter. The Extended Kalman filter uses an approximation model similar to the Taylor series to linearize the functions to obtain the estimation. The linearization is accomplished by taking the
30 partial derivatives of the now non-linear process and

measurement functions, the basis for the two equations in the predict component.

The Extended Kalman filter is governed by the following equations

$$5 \quad x_{k+1} = f(x_k, u_k, w_k) \quad (10)$$

and

$$y_{k+1} = h(x_k, u_k, v_k) \quad (11)$$

where random variables w_k and v_k represent process noise and measurement noise, respectively. Non-linear function f in
 10 equation (10) relates the internal state vector x_k at the current step k to the internal state vector x_{k+1} at the next time step $k+1$. Function f also includes as parameters both the driving function u_k and the process noise w_k . The non-linear function h in equation (11) relates the internal state
 15 vector x_k and input u_k to the measurement y_k .

FIG. 2A and FIG. 2B show the equations of the Extended Kalman Filter. The sequence of operation remains the same as the Kalman filter. There are still two components—predict component 201 and correct component 202. The equations are
 20 slightly different. Specifically, matrices A and C now have a time step sub-script k meaning that they change at each time step. This change is needed because the functions are now non-linear. We can no longer assume that the matrices are constant as in the case of the Kalman filter. To approximate
 25 them, Jacobian matrices are computed by taking partial derivatives of functions f and h at each time step. The Jacobian matrices are listed below.

A is the Jacobian matrix computed by taking the partial derivative of f with respect to x , that is

$$A_{[i,j]_k} = \left. \frac{\partial f_{[i]}}{\partial x_{[j]}} \right|_{x_k = \hat{x}_k} \quad (12)$$

The notation means "with x_k evaluated as, or replaced by, $\hat{x}_k$ in final result."

C is the Jacobian matrix computed by taking the partial
5 derivative of h with respect to x , that is

$$C_{[i,j]_k} = \left. \frac{\partial h_{[i]}}{\partial x_{[j]}} \right|_{x_k = \hat{x}_k} \quad (13)$$

Aside from these additional steps of taking partial
derivatives of functions, the operation of the Extended
Kalman filter remains essentially the same as the Kalman
10 filter.

Using Kalman Filter to Determine the SOC in Batteries

Because it only has to measure the battery output, the
Kalman filter has an advantage in that it works on all types
of batteries system, including dynamic applications such as
15 HEV and EV. There are existing applications that use the
Kalman filter to determine SOC of batteries. However, none of
them uses SOC as an internal state of the model. Thus the
uncertainty associated with the SOC estimation cannot be
determined. The defect is particularly important in HEV and
20 EV batteries where the uncertainty range is needed to prevent
undercharging of battery or loss of vehicle power. Also none
of the existing methods uses the Extended Kalman filter to
model battery SOC non-linearly.

It is important to note that as the Kalman filter is
25 only a generic model. Each application of the Kalman filter
still needs to use a good specific battery model and initial

parameters that accurately describe the behavior of the battery to estimate the SOC. For example, to use the Kalman filter to measure the SOC as an internal state, the filter needs to have a specific equation describing how the SOC transitions from one time step to the next. The determination of such an equation is not trivial.

Using Kalman Filter to Determine the SOH in Batteries

Moreover, in the context of rechargeable battery pack technologies, it is desired in some applications to be able to estimate quantities that are descriptive of the present battery pack condition, but that may not be directly measured. Some of these quantities may change rapidly, such as the pack state-of-charge (SOC), which can traverse its entire range within minutes. Others may change very slowly, such as cell capacity, which might change as little as 20% in a decade or more of regular use. The quantities that tend to change quickly comprise the "state" of the system, and the quantities that tend to change slowly comprise the time varying "parameters" of the system.

In the context of the battery systems, particularly those that need to operate for long periods of time, as aggressively as possible without harming the battery life, for example, in Hybrid Electric Vehicles (HEVs), Battery Electric Vehicles (BEVs), laptop computer batteries, portable tool battery packs, and the like, it is desired that information regarding slowly varying parameters (e.g., total capacity) be available to determine pack health, and to assist in other calculations, including that of state-of-charge (SOC).

There are a number of existing methods for estimating the state-of-health of a cell, which are generally concerned with estimating two quantities: power-fade, and capacity-fade (both slowly time varying). Power fade may be calculated if
5 the present and initial pack electrical resistances are known, and capacity fade may be calculated if present and initial pack total capacities are known, for example, although other methods may also be used. Power- and capacity-fade are often lumped under the description "state-of-health" (SOH). Some
10 other information may be derived using the values of these variables, such as the maximum power available from the pack at any given time. Additional parameters may also be needed for specific applications, and individual algorithms would typically be required to find each one.

15 The prior art uses the following different approaches to estimate SOH: the discharge test, chemistry-dependent methods, Ohmic tests, and partial discharge. The discharge test completely discharges a fully charged cell in order to determine its total capacity. This test interrupts system
20 function and wastes cell energy. Chemistry-dependent methods include measuring the level of plate corrosion, electrolyte density, and "coup de fouet" for lead-acid batteries. Ohmic tests include resistance, conductance and impedance tests, perhaps combined with fuzzy-logic algorithms and/or neural
25 networks. These methods require invasive measurements. Partial discharge and other methods compare cell-under-test to a good cell or model of a good cell.

There is a need for a method to continuously estimate the parameters of a cell, such as the cell's resistance and
30 capacity. Furthermore, there is a need for tests that do not

interrupt system function and do not waste energy, methods that are generally applicable (e.g., to different types of cell electrochemistries and to different applications), methods that do not require invasive measurements, and more
5 rigorous approaches. There is a need for a method that will work with different configurations of parallel and/or series cells in a battery pack.

Disclosure of the Invention

The present invention relates to an implementation of
10 estimating the values descriptive of the packs present operating condition including battery state-of-charge (SOC) and state-of-health (SOH) for any battery-powered application. The batteries may be either primary type or secondary (rechargeable) type. Moreover, the invention may be applied to
15 any battery chemistry. It addresses the problems associated with the existing implementations such as high error uncertainty, limited range of applications (i.e. only one type of battery) and susceptibility to change in temperature.

Embodiments of the present invention use a Kalman Filter,
20 a linear algorithm, with a battery model that has SOC as an internal system state. Embodiments of the present invention use an Extended Kalman Filter, a non-linear algorithm, with a battery model that has SOC as an internal system state. Having SOC as an internal state allows the invention to provide an
25 uncertainty associated with its SOC estimation. Embodiments of the present invention do not take battery temperature as a parameter in its SOC estimation. Other embodiments of the present invention use battery temperature as a parameter to adjust its SOC estimation. This is important to keep the
30 accuracy of the SOC estimation from being affected by changing temperature.

One embodiment has the option of allowing different modeling parameters during battery operation to accommodate highly dynamic batteries used in Hybrid Electric Vehicle (HEV)

and Electric Vehicle (EV) where such previous implementations were difficult.

Further the present invention relates to methods and apparatus for estimating the parameters of an electrochemical cell. More particularly, for example, estimating parameter values of a cell.

Another aspect of the invention is a method for estimating present parameters of an electrochemical cell system comprising: making an internal parameter prediction of the cell; making an uncertainty prediction of the internal parameter prediction; correcting the internal parameter prediction and the uncertainty prediction; and applying an algorithm that iterates the making an internal parameter prediction, the making an uncertainty prediction and the correcting to yield an ongoing estimation to the parameters and an ongoing uncertainty to the parameters estimation.

Also disclosed herein in an exemplary embodiment is a system to estimate present parameters of an electrochemical cell system comprising: a means for making an internal parameter prediction of the cell; a means for making an uncertainty prediction of the internal parameter prediction; a means for correcting the internal parameter prediction and the uncertainty prediction; and a means for applying an algorithm that iterates the making an internal parameter prediction, the making an uncertainty prediction and the correcting to yield an ongoing estimation to the parameters and an ongoing uncertainty to the parameters estimation.

Further, disclosed herein in another exemplary embodiment is a storage medium encoded with a machine-readable computer program code, wherein the storage medium includes instructions for causing a computer to implement a method for estimating present parameters of an electrochemical cell comprising: making an internal parameter prediction of the cell; making an uncertainty prediction of the internal parameter prediction;

correcting the internal parameter prediction and the uncertainty prediction; and applying an algorithm that iterates making an internal parameter prediction, making an uncertainty prediction and correcting to yield an ongoing
5 estimation to the parameters and an ongoing uncertainty to the parameters estimation.

BRIEF DESCRIPTION OF THE DRAWINGS

These and other features, aspects and advantages of the present invention will become better understood with regard to
10 the following description, appended claims and accompanying drawings wherein like elements are numbered alike in the several Figures:

FIG. 1 shows the operation of a generic Kalman Filter.

FIG. 1A shows the equations of a predict component of a
15 generic Kalman Filter.

FIG. 1B shows the equations of a correct component of a generic Kalman Filter.

FIG. 2A shows the equations of the predict component of a generic Extended Kalman Filter.

20 FIG. 2B shows the equations of the correct component of a generic Extended Kalman Filter.

FIG. 3A shows the components of the SOC estimator according to an embodiment of the present invention.

FIG. 3B shows the components of the SOC estimator
25 according to another embodiment of the present invention.

FIG. 4A shows the equations of the predict component of an implementation of the Extended Kalman Filter according to an embodiment of the present invention.

FIG. 4B shows the equations of the correct component of
30 an implementation of the Extended Kalman Filter according to an embodiment of the present invention.

FIG. 5A shows the equations of the predict component of an implementation of the Extended Kalman Filter according to an embodiment of the present invention.

FIG. 5B shows the equations of the correct component of an implementation of the Extended Kalman Filter according to an embodiment of the present invention.

FIG. 6 shows the operation of an Extended Kalman Filter
5 according to an embodiment of the present invention.

FIG. 7 shows the operation of an Extended Kalman Filter according to another embodiment of the present invention.

FIG. 8A shows the equations of the predict component of an implementation of the Kalman Filter according to an
10 embodiment of the present invention.

FIG. 8B shows the equations of the correct component of an implementation of the Kalman Filter according to an embodiment of the present invention.

FIG. 9 shows the operation of a Kalman Filter according
15 to an embodiment of the present invention.

FIG. 10 shows the operation of an embodiment of the present invention that dynamically changes the modeling equations for the battery SOC.

FIG. 11 is a block diagram illustrating an exemplary
20 system for parameter estimation in accordance with an exemplary embodiment of the invention.

FIG. 12 is a block diagram depicting a method of filtering for parameter estimation, in accordance with an exemplary embodiment of the invention.

Best Mode for Carrying Out the InventionImplementation of a Battery State-of-Charge (SOC)Estimating

Embodiments of the present invention relate to an
5 implementation of a battery state-of-charge (SOC) estimator
for any battery-powered application.

The present invention may be applied to batteries of
primary type or secondary (rechargeable) type. The invention
may be applied to any battery chemistry. Embodiments of the
10 present invention work on dynamic batteries used in Hybrid

Electric Vehicle (HEV) and Electric Vehicle (EV) where previous implementations were difficult. It has the advantage of giving both the SOC estimate and the uncertainty of its estimation. It addresses the problems associated with the existing implementations such as high error uncertainty, limited range of applications and susceptibility to temperature changes.

Temperature-Independent Model

FIG. 3A shows the components of the SOC estimator according an embodiment of the present invention. Battery 301 is connected to load circuit 305. For example, load circuit 305 could be a motor in an Electric Vehicle (EV) or a Hybrid Electric Vehicle (HEV). Measurements of battery terminal voltage are made with voltmeter 302. Measurements of battery current are made with ammeter 303. Voltage and current measurements are processed with arithmetic circuit 304, which estimates the SOC. Note that no instrument is needed to take measurements from the internal chemical components of the battery. Also note that all measurements are non-invasive; that is, no signal is injected into the system that might interfere with the proper operation of load circuit 305.

Arithmetic circuit 304 uses a mathematical model of the battery that includes the battery SOC as a model state. In one embodiment of the present invention, a discrete-time model is used. In another embodiment a continuous-time model is used. In one embodiment, the model equations are

$$x_{k+1} = f(x_k, i_k, w_k) \quad (14)$$

and

$$y_{k+1} = h(x_k, i_k, v_k) \quad (15)$$

where x_k is the model state at time index k (x_k may either be a scalar quantity or a vector), i_k is the battery current at time index k , and w_k is a disturbance input at time index k . The function $f(x_k, i_k, w_k)$ relates the model state at time index k to the model state at time index $k+1$, and may either be a linear or nonlinear function. Embodiments of the present invention have the battery SOC as an element of the model state vector x_k .

In equation (15), the variable v_k is the measurement noise at time index k , and y_k is the model's prediction of the battery terminal voltage at time index k . The function $h(x_k, i_k, w_k)$ relates the model's state, current and measurement noise to the predicted terminal voltage at time index k . This function may either be linear or nonlinear. The period of time that elapses between time indices is assumed to be fixed, although the invention allows measurements to be skipped from time to time.

Temperature-Dependent Model

FIG. 3B shows the components of the SOC estimator according another embodiment of the present invention. Battery 351 is connected to load circuit 355. For example, load circuit 355 could be a motor in an Electric Vehicle (EV) or Hybrid Electric Vehicle (HEV). Measurements of battery terminal voltage are made with voltmeter 352. Measurements of battery current are made with ammeter 353. Battery temperature is measured by temperature sensor 356. Voltage, current and temperature measurements are processed with arithmetic circuit 354, which estimates the SOC.

Arithmetic circuit 354 uses a temperature dependent mathematical model of the battery that includes the battery

SOC as a model state. In one embodiment of the present invention, a discrete-time model is used. In another embodiment a continuous-time model is used. In one embodiment, the model equations are

$$5 \quad x_{k+1} = f(x_k, i_k, T_k, w_k) \quad (16)$$

and

$$y_{k+1} = h(x_k, i_k, T_k, v_k) \quad (17)$$

where x_k is the model state at time index k (x_k may either be a scalar quantity or a vector), T_k is the battery temperature at time index k measured at one or more points within the battery pack, i_k is the battery current at time index k , and w_k is a disturbance input at time index k . The use of battery temperature as a dependent parameter is important to keep the accuracy of the SOC estimation from being affected by changing temperature. The function $f(x_k, i_k, T_k, w_k)$ relates the model state at time index k to the model state at time index $k+1$, and may either be a linear or nonlinear function. Embodiments of the present invention have the battery SOC as an element of the model state vector x_k .

20 In equation (17), the variable v_k , is the measurement noise at time index k , and y_k is the model's prediction of the battery terminal voltage at time index k . The function $h(x_k, i_k, T_k, v_k)$ relates the model's state, current and measurement noise to the predicted terminal voltage at time index k . This function may either be linear or nonlinear. The period of time that elapses between time indices is assumed to be fixed, although the invention allows measurements to be skipped from time to time.

30 Applying the Models to Kalman Filter and Extended Kalman Filter

In one embodiment of the present invention, the temperature-independent mathematical battery model of equations (14) and (15) is used as the basis for a Kalman filter to estimate the battery SOC as the system operates. The functions f and h in this embodiment are linear. In another embodiment of the present invention, the temperature-dependent mathematical battery model of equations (16) and (17) is used as the basis for a Kalman filter to estimate the battery SOC as the system operates. The functions f and h in this embodiment are also linear.

In another embodiment of the present invention, the temperature-independent mathematical battery model of equations (14) and (15) is used as a basis for an Extended Kalman filter. The functions f and h in this embodiment are non-linear. In another embodiment of the present invention, the temperature-dependent mathematical battery model of equations (16) and (17) is used as a basis for an Extended Kalman filter. The functions f and h in this embodiment are also non-linear. Those skilled in the art will recognize that other variants of a Kalman filter may also be used, as well as any Luenberger-like observer.

The Operation of the Extended Kalman Filter

FIG. 4A and FIG. 4B show an embodiment with an Extended Kalman filter. In this embodiment, equations (14) and (15) from the temperature-independent model is used as the basis of the Extended Kalman filter. Within the two figures, the equations within both the predict and correct components retain the generic form of the Extended Kalman Filter as shown in FIG. 2. However, in this embodiment there is some variation in the variable names. The differences reflect the

use of equations (14) and (15) and the variables used in the battery SOC measurement. $\hat{x}_k(-)$ now represents the predicted vector representing the internal states of the battery while $\Sigma_{e,k}(-)$ is now the predicted state-error covariance (uncertainty). The functions f and h are the same as those described in equations (14) and (15). Note also that in equation 462 of correct component 402, the actual measurement term is now denoted by m_k .

FIG. 5A and FIG. 5B show another embodiment with an Extended Kalman filter. In this embodiment, equations (16) and (17) from the temperature-dependent model is used as the basis of the Extended Kalman filter. All the equations are the same as those in FIG. 4A and FIG. 4B except that equation 551 and 562 now have an extra temperature term T_k . Thus at every iteration of the Extended Kalman filter in this embodiment, the temperature of the battery is used to determine the estimation. Since battery capacity is sometimes affected by the temperature, this extra term allows the equations to model the battery more accurately.

FIG. 6. shows the operation of the Extended Kalman filter according to an embodiment of the present invention that uses the temperature-independent model. In block 600, an algorithm is initialized with prior estimates of $\hat{x}_k(-)$ and $\Sigma_{e,k}(-)$. $\hat{x}_k(-)$ is from function f in equation (14) while $\Sigma_{e,k}(-)$ is from function h in equation (15). Upon the completion of block 600, with the estimates of $\hat{x}_k(-)$ and $\Sigma_{e,k}(-)$ the algorithm enters correct component of the Extended Kalman filter. The estimates $\hat{x}_k(-)$ and $\Sigma_{e,k}(-)$ serve as the output from the predict component needed by the correct component. In block 601, the partial derivative of the equation h with respect to x is

computed, yielding matrix C . In block 602, the Kalman gain L_k is computed using matrix C , $\hat{x}_k(-)$ and $\Sigma_{e,k}(-)$. This corresponds to the first equation (equation 461) of correct component 402 in FIG. 4B. Then in block 603, the predicted internal state vector $\hat{x}_k(-)$, the Kalman gain L_k and the measurement from terminal voltage m_k are used to calculate a corrected state vector $\hat{x}_k(+)$. This corresponds to the second equation of the correct component in the Extended Kalman filter. In block 604, the predicted state-error covariance $\Sigma_{e,k}(-)$ is used to compute a corrected state-error covariance $\Sigma_{e,k}(+)$. This corresponds to the third equation of the correct component.

In block 605, both of the equations of the predict component are computed. The matrix A is computed by taking the partial derivative of the function f with respect to x . Then the prediction for the next iteration is computed, namely $\hat{x}_{k+1}(-)$ and $\Sigma_{e,k+1}(-)$. In block 606 the time index k is incremented and the operation begins in block 601 again with the next time step.

FIG. 7. shows the operation of the Extended Kalman filter according to another embodiment of the present invention that uses the temperature-dependent model. In block 700, an algorithm is initialized with prior estimates of $\hat{x}_k(-)$ and $\Sigma_{e,k}(-)$ is from function f in equation (16) while $\Sigma_{e,k}(-)$ is from function h in equation (17). Upon the completion of block 700, with the estimates of $\hat{x}_k(-)$ and $\Sigma_{e,k}(-)$, the algorithm enters correct component of the Extended Kalman filter. The estimates $\hat{x}_k(-)$ and $\Sigma_{e,k}(-)$ serve as the output from the predict component needed by the correct component. In block 701, the partial derivative of the equation h with respect to x is computed, yielding matrix C . In block 702,

the Kalman gain L_k is computed using matrix C , $\hat{x}_k(-)$ and $\Sigma_{e,k}(-)$. This corresponds to the first equation (equation 561) of correct component 502 in FIG 5B. Then in block 703, the predicted internal state vector $\hat{x}_k(-)$, the Kalman gain L_k and the measurement from terminal voltage m_k are used to calculate a corrected state vector $\hat{x}_k(+)$. This corresponds to the second equation of the correct component in the Extended Kalman filter. In block 704, the predicted state-error covariance $\Sigma_{e,k}(-)$ is used to compute a corrected state-error covariance $\Sigma_{e,k}(+)$. This corresponds to the third equation of the correct component.

In block 705, both of the equations of the predict component are computed. The matrix A is computed by taking the partial derivative of the function f with respect to x . Then the prediction for the next iteration is computed, namely $\hat{x}_{k+1}(-)$ and $\Sigma_{e,k+1}(-)$. In block 706 the time index k is incremented and the operation begins in block 701 again with the next time step.

The Operation of the Kalman Filter

FIG. 8A and FIG. 8B show an embodiment with a Kalman filter. In one embodiment, equations (14) and (15) from the temperature-independent model is used as the basis of the Kalman filter. In another embodiment, equations (16) and (17) from the temperature-dependent model is used as the basis of the Kalman filter. Within the two figures, the equations within both the predict and correct components retain the generic form of the Kalman Filter as shown in FIG.1. However, in this embodiment there is some variation in the variable names. In one embodiment, the differences reflect the use of equations (14) and (15) and the variables used in the battery

SOC measurement. In another embodiment, the differences reflect the use of equations (16) and (17) and the variables used in the battery SOC measurement. $\hat{x}_k(-)$ now represents the predicted vector representing the internal states of the battery while $\Sigma_{e,k}(-)$ is now the predicted state-error covariance (uncertainty). Note also that in equation 862 of correct component 802, the actual measurement term is now denoted by m_k .

FIG. 9 shows the operation of the Kalman filter according to an embodiment of the present invention. In block 900, an algorithm is initialized with prior estimates of $\hat{x}_k(-)$ and $\Sigma_{e,k}(-)$. In one embodiment, $\hat{x}_k(-)$ is from function f in equation (14) while $\Sigma_{e,k}(-)$ is from function h in equation (15). This embodiment is temperature-independent. In another embodiment, $\hat{x}_k(-)$ is from function f in equation (16) while $\Sigma_{e,k}(-)$ is from function h in equation (17). This embodiment is temperature-dependent. Upon the completion of block 900, with the estimates of $\hat{x}_k(-)$ and $\Sigma_{e,k}(-)$, the algorithm enters correct component of the Kalman filter. The estimates $\hat{x}_k(-)$ and $\Sigma_{e,k}(-)$ serve as the output from the predict component needed by the correct component. In block 901 the Kalman gain L_k is computed using matrix C , $\hat{x}_k(-)$ and $\Sigma_{e,k}(-)$. This corresponds to the first equation (equation 861) of correct component 802 in FIG. 8B. Then in block 902 the predicted internal state vector $\hat{x}_k(-)$, the Kalman gain L_k and the measurement from terminal voltage m_k are used to calculate a corrected state vector $\hat{x}_k(+)$. This corresponds to the second equation of the correct component in the Kalman filter. In block 903, the predicted state-error covariance $\Sigma_{e,k}(-)$ is used to compute a corrected state-error covariance $\Sigma_{e,k}(+)$. This corresponds to

the third equation of the correct component. In block 904, both of the equations of the predict component are calculated. Then the prediction for the next iteration is computed, namely $\hat{x}_{k+1}(-)$ and $\Sigma_{e,k+1}(-)$. In block 905 the time index k is
 5 incremented and the operation begins in block 901 again with the next time step.

Specific Equations

In one embodiment, the following specific form of function f is used. The internal state vector x_k is:

$$10 \quad x_k = \begin{bmatrix} SOC_k \\ FILT_k \\ IFI_k \\ IF2_k \end{bmatrix} \quad (18)$$

and the governing equation for each state is:

$$SOC_{k+1} = SOC_k - \eta(I_k)|I_k|^n \Delta t / C_p(temp...)$$

$$FILT_{k+1} = SOC_k + k_i FILT_k + k_s$$

$$IFI_{k+1} = \begin{bmatrix} a_1 & a_2 \\ -a_2 & a_1 \end{bmatrix} IF_k + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \eta(I_k)|I_k|^n \Delta t / C_p(temp...). \quad (19)$$

The battery SOC is the first element of the state vector. The variables are defined as follows: I_k is the instantaneous
 15 current, Δt is the interval between time instants, C_p (temp . . .) is the "Peukert" capacity of the battery adjusted to be temperature-dependent, n is the Peukert exponent related to the Peukert. capacity, and $\eta(I_k)$ is the battery coulombic efficiency as a function of current. The
 20 state variables $FILT$ and IF are filter states that capture most of the smooth slow dynamics of the battery.

In one embodiment, the following specific form of function h is used:

$$y_k = k_0 \text{FILT}_k + k_1 + k_2 I_k + k_3 (SOC_k + k_5) + k_4 SOC_k + [c_1 c_2] I F_k \quad (20)$$

where y_k is the terminal voltage. All other variables (k_0, k_1 , etc) are coefficients of the model, which may be determined a priori from lab tests and may be adjusted during system operation using mechanisms not discussed here. These coefficients vary in the present invention so that the coefficients used for an instantaneous discharge of 10 Amps would be different from those used for an instantaneous charge of 5 Amps, for example. This allows the invention to more precisely model the current-dependence of the model.

In another embodiment, the following form of function f is used. The internal state vector x_k is

$$x_k = \begin{bmatrix} SOC_k \\ SOC_{k-1} \\ \vdots \\ SOC_{k-\alpha} \\ i_k \\ i_{k-1} \\ \vdots \\ i_{k-\beta} \\ y_{k-1} \\ y_{k-2} \\ \vdots \\ y_{k-\gamma} \end{bmatrix} \quad (21)$$

where SOC_k is the present SOC estimate, SOC_{k-1} is the previous SOC estimate (and so forth), i_k is the present current measurement (and so forth) and y_{k-1} is the previous

battery voltage estimate. α , β and γ are positive constants chosen to make an acceptable model with a parsimonious number of state variables. The governing equation for the SOC state is:

$$5 \quad SOC_{k+1} = SOC_k - \eta(I_k) |I_k|^n \Delta t / C_p(temp \dots) \quad (22)$$

In the embodiment, the specific form of function h is used

$$y_k = h(x_k, T_k), \quad (23)$$

where h is implemented as a nonlinear function fit to
 10 measured data. For example, h may be implemented using a neural network.

In one embodiment a neural network may be used to estimate the internal states of the battery. The difference between this embodiment and prior neural networks is as
 15 follows. In prior art neural networks, the estimated SOC is the output of the neural networks. This embodiment indirectly measures the SOC by first modeling the battery cell using a neural network with SOC as one of its states, and then uses a Kalman filter with the neural network to estimate SOC. This
 20 approach has two main advantages. First it can be trained on-line while it is in operation. Second, error bounds on the estimate may be computed.

Changing Parameters

FIG. 10 shows the operation of an embodiment of the
 25 present invention that dynamically changes modeling equations for the battery SOC. In this embodiment, the arithmetic circuit can accommodate changing behaviors of the battery to use different parameters for different time periods. In block 11000, a change in battery current level is detected. For

example, in a Hybrid Electric Vehicle (HEV), a sudden drain in the battery power is caused by the vehicle going uphill. The sudden change in condition triggers the arithmetic circuit to use a different set of modeling equations to more accurately estimate the SOC in the new condition. In block 1010 a new set of modeling equations are used. In 1020, the new equations are used to determine the SOC. This adaptive modeling behavior is useful in highly dynamic applications such as in Hybrid Electric Vehicles (HEV) and Electric Vehicles (EV).

Further, disclosed herein and various embodiments are methods, systems and apparatus for the estimation of parameters of an electrochemical cell using filtering are disclosed. Referring now to FIG. 11 and FIG. 12, in the following description, numerous specific details are set forth in order to provide a more complete understanding of the present invention. It will be appreciated that while the exemplary embodiments are described with reference to a battery cell, numerous electrochemical cells hereinafter referred to as a cell, may be employed, including, but not limited to, batteries, battery packs, ultracapacitors, capacitor banks, fuel cells, electrolysis cells, and the like, as well as combinations including at least one of the foregoing. Furthermore, it will be appreciated that a battery or battery pack may include a plurality of cells, where the exemplary embodiments disclosed herein are applied to one or more cells of the plurality.

One or more exemplary embodiments of the present invention estimate cell parameter values using a filtering method. One or more exemplary embodiments of the present

invention estimate cell parameter values using Kalman filtering. Some embodiments of the present invention estimate cell parameter values using extended Kalman filtering. Some embodiments estimate cell resistance. Some
5 embodiments estimate cell total capacity. Some embodiments estimate other time-varying parameter values. It will further be appreciated that while the term filtering is employed for description and illustration of the exemplary embodiments, the terminology is intended to include
10 methodologies of recursive prediction and correction commonly denoted as filtering, including but not limited to Kalman filtering and/or extended Kalman filtering.

Implementation of a Battery State of Health (SOH)
Estimating

15 FIG. 11 shows the components of the parameter estimator system 10 according an embodiment of the present invention. Electrochemical cell pack 20 comprising a plurality of cells 22, e.g., battery is connected to a load circuit 30. For example, load circuit 30 could be a motor in an Electric
20 Vehicle (EV) or a Hybrid Electric Vehicle (HEV). An apparatus for measuring various cell characteristics and properties is provided as 40. The measurement apparatus 40 may include but not be limited to a device for measurement of cell terminal voltage such as a voltage sensor 42, e.g. a
25 voltmeter and the like, while measurements of cell current are made with a current sensing device 44, e.g., an ammeter and the like. Optionally, measurements of cell temperature are made with a temperature sensor 46, e.g., a thermometer and the like. Additional cell properties, such as internal
30 pressure or impedance, may be measured using (for example)

pressure sensors and/or impedance sensors 48 and may be employed for selected types of cells. Various sensors may be employed as needed to evaluate the characteristics and properties of the cell(s). Voltage, current, and optionally
5 temperature and cell-property measurements are processed with an arithmetic circuit 50, e.g., processor or computer, which estimates the parameters of the cell(s). The system may also include a storage medium 52 comprising any computer usable storage medium known to one of ordinary skill in the art.
10 The storage medium is in operable communication with arithmetic circuit 50 employing various means, including, but not limited to a propagated signal 54. It should be appreciated that no instrument is required to take measurements from the internal chemical components of the
15 cell 22 although such instrumentation may be used with this invention. Also note that all measurements may be non-invasive; that is, no signal must be injected into the system that might interfere with the proper operation of load circuit 30.

20 In order to perform the prescribed functions and desired processing, as well as the computations therefore (e.g., the modeling, estimation of parameters prescribed herein, and the like), arithmetic circuit 50 may include, but not be limited to, a processor(s), gate array(s), custom logic, computer(s),
25 memory, storage, register(s), timing, interrupt(s), communication interfaces, and input/output signal interfaces, as well as combinations comprising at least one of the foregoing. Arithmetic circuit 50 may also include inputs and input signal filtering and the like, to enable accurate
30 sampling and conversion or acquisitions of signals from

communications interfaces and inputs. Additional features of arithmetic circuit 50 and certain processes therein are thoroughly discussed at a later point herein.

One or more embodiments of the invention may be implemented as new or updated firmware and software executed in arithmetic circuit 50 and/or other processing controllers. Software functions include, but are not limited to firmware and may be implemented in hardware, software, or a combination thereof. Thus a distinct advantage of the present invention is that it may be implemented for use with existing and/or new processing systems for electrochemical cell charging and control.

In an exemplary embodiment, Arithmetic circuit 50 uses a mathematical model of the cell 22 that includes indicia of a dynamic system state. In one embodiment of the present invention, a discrete-time model is used. An exemplary model for the cell 22 in a (possibly nonlinear) discrete-time state-space form has the form:

$$\begin{aligned} x_{k+1} &= f(x_k, u_k, \theta_k) + w_k \\ y_k &= g(x_k, u_k, \theta_k) + v_k, \end{aligned} \tag{24}$$

where x_k is the system state, θ_k is the set of time varying model parameters, u_k is the exogenous input, y_k is the system output, and w_k and v_k are "noise" inputs—all quantities may be scalars or vectors. $f(·,·)$ and $g(·,·)$ are functions defined by the cell model being used. Non-time-varying numeric values required by the model may be embedded within $f(·,·)$ and $g(·,·)$, and are not included in θ_k .

The system state x_k includes, at least, a minimum amount of information, together with the present input and a mathematical model of the cell, needed to predict the present

output. For a cell 22, the state might include: SOC, polarization voltage levels with respect to different time constants, and hysteresis levels, for example. The system exogenous input u_k includes at minimum the present cell
5 current i_k , and may, optionally, include cell temperature (unless temperature change is itself modeled in the state). The system parameters θ_k are the values that change only slowly with time, in such a way that they may not be directly determined with knowledge of the system measured input and
10 output. These might include, but not be limited to: cell capacity, resistance, polarization voltage time constant(s), polarization voltage blending factor(s), hysteresis blending factor(s), hysteresis rate constant(s), efficiency factor(s), and so forth. The model output y_k corresponds to physically
15 measurable cell quantities or those directly computable from measured quantities at minimum for example, the cell voltage under load.

There are a number of existing methods for estimating the state of a cell including, but not limited to the state
20 charge of a cell 22. SOC is a value, typically reported in percent, which indicates the fraction of the cell capacity presently available to do work. A number of different approaches to estimating SOC have been employed: a discharge test, ampere-hour counting (Coulomb counting), measuring the
25 electrolyte, open-circuit voltage measurement, linear and nonlinear circuit modeling, impedance spectroscopy, measurement of internal resistance, coup de fouet, and some forms of Kalman filtering. Each of these methodologies exhibits advantages as well as limitations.

According to the above embodiments of the present invention related to an implementation of a battery State of Charge (SOC) estimator, a filter, preferably a Kalman filter is used to estimate SOC by employing a known mathematical
 5 model of cell dynamics and measurements of cell voltage, current, and temperature. Advantageously, this method directly estimates state values for the cell where SOC is at least one of the states. However, it should be appreciated that there are numerous well-known methodologies for
 10 computing SOC.

Continuing with FIG. 12, a mathematical model of parameter dynamics is also utilized. An exemplary model has the form:

$$\begin{aligned}\theta_{k+1} &= \theta_k + r_k \\ d_k &= g(x_k, u_k, \theta_k) + e_k.\end{aligned}\tag{25}$$

15 The first equation states that the parameters θ_k are primarily constant, but that they may change slowly over time, in this instance, modeled by a "noise" process denoted, r_k . The "output" d_k is a function of the optimum parameter dynamics modeled by $g(:, :)$ plus some estimation error e_k . The
 20 optimum parameter dynamics $g(:, :)$ being a function of the system state x_k , an exogenous input u_k , and the set of time varying parameters θ_k .

With a model of the cell system, requirements for state dynamics, and model of the parameter dynamics defined, in an
 25 exemplary embodiment, a procedure of filtering is applied. Once again, alternatively, a Kalman filter may be employed, or an extended Kalman filter. Table 1 identifies an exemplary implementation of the methodology and system utilizing an extended Kalman filter 1100. Once again, it

should be appreciated that while the cell model and parameter estimation models employ the state x_k of the cell 22, the state is not necessarily predicted as part of the parameter estimation process. For example, in one exemplary embodiment, the state x_k of the cell 22, is computed by another process with the resulting state information supplied to the parameters model. Continuing with an exemplary implementation of Table 1, the procedure is initialized by setting a parameter estimate, denoted $\hat{\theta}$ to the best guess of the true parameters, e.g., $\hat{\theta} = E[\theta_0]$. While not required or defined for the state estimate, the state estimate denoted $\hat{x}$ may be set to the best estimate of the cell state, e.g., $\hat{x} = E[x_0]$. An estimation-error covariance matrix $\Sigma_{\hat{\theta}}^+$ is also initialized. For example, an initialization of state, and particularly, SOC might be estimated/based on a cell voltage in a look-up table, or information that was previously stored when a battery pack/cell was last powered down. Other examples might incorporate the length of time that the battery system had rested since power-down and the like.

Table 1: Extended Kalman filter for parameter update.

State-space models:

$$\begin{aligned} x_{k+1} &= f(x_k, u_k, \theta_k) + w_k & \text{and} & & \theta_{k+1} &= \theta_k + r_k \\ y_k &= g(x_k, u_k, \theta_k) + v_k & & & d_k &= g(x_k, u_k, \theta_k) + e_k, \end{aligned}$$

where w_k , v_k , r_k and e_k are independent, zero-mean, Gaussian noise processes of covariance matrices Σ_w , Σ_v , Σ_r and Σ_e , respectively.

Definition:

$$C_k^{\theta} = \left. \frac{dg(\hat{x}_k^-, u_k, \theta)}{d\theta} \right|_{\theta = \hat{\theta}_k^-}$$

Initialization: For $k=0$, set

$$\hat{\theta}_0^+ = E[\theta_0], \quad \Sigma_{\hat{\theta},0}^+ = E[(\theta_0 - \hat{\theta}_0^+)(\theta_0 - \hat{\theta}_0^+)^T]$$

Computation: For $k=1,2,\dots$, compute:

Time update

$$\hat{\theta}_k^- = \hat{\theta}_{k-1}^+$$

$$\Sigma_{\tilde{\theta},k}^- = \Sigma_{\tilde{\theta},k-1}^+ + \Sigma_r$$

Measurement update

$$L_k^\theta = \Sigma_{\tilde{\theta},k}^- (C_k^\theta)^T [C_k^\theta \Sigma_{\tilde{\theta},k}^- (C_k^\theta)^T + \Sigma_e]^{-1}$$

$$\hat{\theta}_k^+ = \hat{\theta}_k^- + L_k^\theta [y_k - g(f(\hat{x}_{k-1}, u_{k-1}, \hat{\theta}_k^-), u_k, \hat{\theta}_k^-)]$$

$$\Sigma_{\tilde{\theta},k}^+ = (I - L_k^\theta C_k^\theta) \Sigma_{\tilde{\theta},k}^-.$$

In this example, several steps are performed in each measurement interval. First, the previous parameter estimate is propagated forward in time. The new parameter estimate is equal to the old parameter estimate $\hat{\theta}_k^- = \hat{\theta}_{k-1}^+$, and the parameter error uncertainty is larger due to the passage of time (accommodated for in the model by the driving noise r_k). It should be readily appreciated that various possibilities exist for updating the parameter uncertainty estimate, the table provides an illustrative example. A measurement of the cell output is made, and compared to the predicted output based on the state estimate, $\hat{x}$ (however estimated or provided) and parameter estimate, $\hat{\theta}$; the difference is used to update the values of $\hat{\theta}$. Note also, the state estimate $\hat{x}$ may be propagated forward by the parameter estimate or may be supplied via an external means as identified above. C_k^θ may be computed using the following recurrence relationship:

$$\begin{aligned} \frac{dg(x_k, u_k, \theta)}{d\theta} &= \frac{\partial g(x_k, u_k, \theta)}{\partial \theta} + \frac{\partial g(x_k, u_k, \theta)}{\partial x_k} \frac{dx_k}{d\theta}, \\ \frac{dx_k}{d\theta} &= \frac{\partial f(x_{k-1}, u_{k-1}, \theta)}{\partial \theta} + \frac{\partial f(x_{k-1}, u_{k-1}, \theta)}{\partial x_{k-1}} \frac{dx_{k-1}}{d\theta}. \end{aligned} \quad (26)$$

The derivative calculations are recursive in nature, and evolve over time as the state x_k evolves. The term $dx_0/d\theta$ is initialized to zero unless side information yields a better

estimate of its value. It may readily be appreciated that the steps outlined in the table may be performed in a variety of orders. While the table lists an exemplary ordering for the purposes of illustration, those skilled in the art will
 5 be able to identify many equivalent ordered sets of equations.

Turning now to FIG. 12 as well, an exemplary implementation of an exemplary embodiment of the invention is depicted. A recursive filter 1100 adapts the parameter estimate, $\hat{\theta}$. The filter has a time update or prediction
 10 1103 aspect and a measurement update or correction 1104 aspect. Parameter time update/prediction block 1103 receives as input the previous exogenous input u_{k-1} , the previous time varying parameters estimate $\hat{\theta}_{k-1}^+$ and a corrected parameter uncertainty estimate $\Sigma_{\hat{\theta},k-1}^+$. Parameter time update/prediction
 15 block 1103 outputs predicted parameters $\hat{\theta}_k^-$ and predicted parameter uncertainty $\Sigma_{\hat{\theta},k}^-$ to the parameter measurement update/correction block 1104. Parameter measurement update block 1104, which provides current parameter estimate $\hat{\theta}_k^+$ and parameter uncertainty estimate, $\Sigma_{\hat{\theta},k}^+$ receives the predicted
 20 parameters $\hat{\theta}_k^-$ and predicted parameter uncertainty $\Sigma_{\hat{\theta},k}^-$ as well as the exogenous input u_k and the modeled system output y_k . It will also be appreciated that a minus notation denotes that the vector is the result of the prediction component 1103 of the filter 1100, while the plus notation denotes that
 25 the vector is the result of the correction component 1104 of the filter 1100.

Embodiments of this invention require a mathematical model of cell state and output dynamics for the particular application. In the exemplary embodiments, this is accomplished by defining specific functions for $f(:,:)$ and $g(:,:)$ to facilitate estimation or receipt of the various states and estimation of the various parameters of interest. An exemplary embodiment uses a cell model that includes effects due to one or more of the open-circuit-voltage (OCV) for the cell, internal resistance, voltage polarization time constants, and a hysteresis level. For the purpose of example, parameter values are fitted to this model structure to model the dynamics of high-power Lithium-Ion Polymer Battery (LiPB) cells, although the structure and methods presented here are general and apply to other electrochemistries. For example, in an exemplary embodiment, the states and parameters of interest are embedded in $f(:,:)$ and $g(:,:)$, and examples follow:

$$\theta_k = \left[\eta_{i,k}, C_k, a_{1,k} \cdots a_{n_f,k}, g_{1,k} \cdots g_{n_f-1,k}, \gamma_k, R_k, M_k \right]^T. \quad (27)$$

where $\eta_{i,k}$ is an efficiency factor(s) such as Coulombic efficiency,
 C_k is the cell capacity/capacities,
 $a_{1,k}, \dots, a_{n_f,k}$ are polarization voltage time constant(s),
 $g_{1,k}, \dots, g_{n_f-1,k}$ are the polarization voltage blending factor(s),
 R_k is the cell resistance(s),
 M_k is the hysteresis blending factor(s), and
 γ_k is the hysteresis rate constant(s).

In this example, SOC is captured by one state of the model as part of function $f(:,:)$. This equation is:

$$z_{k+1} = z_k - (\eta_{i,k} \Delta t / C_k) i_k \quad (28)$$

where Δt represents the inter-sample period (in seconds), C_k represents the cell capacity (in ampere-seconds), z_k is the cell SOC at time index k , i_k is the cell current, and $\eta_{i,k}$ is the Coulombic efficiency of a cell at current level i_k .

In this example, the polarization voltage levels are captured by several filter states. If we let there be n_f polarization voltage time constants, then

$$f_{k+1} = A_f f_k + B_f i_k. \quad (29)$$

The matrix $A_f \in \mathbb{R}^{n_f \times n_f}$ may be a diagonal matrix with real-valued polarization voltage time constants $a_{1,k} \cdots a_{n_f,k}$. If so, the system is stable if all entries have magnitude less than one. The vector $B_f \in \mathbb{R}^{n_f \times 1}$ may simply be set to n_f "1"s. The entries of B_f are not critical as long as they are non-zero. The value of n_f entries in the A_f matrix are chosen as part of the system identification procedure to best fit the model parameters to measured cell data. The A_f , and B_f matrices may vary with time and other factors pertinent to the present battery pack operating condition.

In this example, the hysteresis level is captured by a single state

$$h_{k+1} = \exp\left(-\left|\frac{\eta_{i,k} i_k \gamma_k \Delta t}{C_k}\right|\right) h_k + \left(1 - \exp\left(-\left|\frac{\eta_{i,k} i_k \gamma_k \Delta t}{C_k}\right|\right)\right) \text{sgn}(i_k), \quad (30)$$

where γ_k is the hysteresis rate constant, again found by system identification.

In yet another exemplary embodiment, the overall model state is a combination of the above examples as follows:

$$x_k = \begin{bmatrix} f_k^T & h_k & z_k \end{bmatrix}^T, \quad (31)$$

where other orderings of states are possible.

In this example, the output equation that combines the state values to predict cell voltage is

$$v_k = \text{OCV}(z_k) + G_k f_k - R_k i_k + M_k h_k, \quad (32)$$

5 where $G_k \in \mathbb{R}^{1 \times n_f}$ is a vector of polarization voltage blending factors $g_{1,k} \cdots g_{n_f,k}$ that blend the polarization voltage states together in the output, R_k is the cell resistance (different values may be used for discharge/charge), and M_k is the hysteresis blending factor. Note, G_k may be constrained such
10 that the dc-gain from i_k to $G_k f_k$ is zero, which results in the estimates of R_k being accurate.

Some embodiments of the present invention may include methods to constrain the parameters of the model to result in a stable system. In an exemplary embodiment, the state
15 equation may include terms for polarization voltage time constants in the form $f_{k+1} = A_f f_k + B_f i_k$, where the matrix $A_f \in \mathbb{R}^{n_f \times n_f}$ is diagonal matrix with real-valued polarization voltage time constants $a_{1,k} \cdots a_{n_f,k}$. These time constants may be computed as $a_{i,k} = \tanh(\alpha_{i,k})$, where the parameter vector of the model contains
20 the $\alpha_{i,k}$ values and not directly the $a_{i,k}$ values. The $\tanh()$ function ensures that the $a_{i,k}$ are always within ± 1 (i.e., stable) regardless of the value of $\alpha_{i,k}$.

Some embodiments of the present invention include constraints to the model to ensure convergence of a parameter
25 to its correct value. An exemplary embodiment using the model herein described constrains G_k so that the dc-gain from i_k to $G_k f_k$ is zero, which results in the estimates of R_k being accurate. This is done by enforcing that the last element of G_k be computed using other elements of G_k and the

polarization voltage time constants $g_{n_f,k} = -\sum_{i=1}^{n_f-1} g_{i,k}(1-a_{n_f,k})/(1-a_{i,k})$.

This also requires more care when computing elements of C_k^θ

relating to G_k : $\frac{\partial g(x_k, u_k, \theta)}{\partial g_{i,k}} = f_{k,i} - \frac{1-a_{n_f,k}}{1-a_{i,k}} f_{k,n_f}, 1 \leq i < n_f$. If the $a_{i,k}$

values are always within ± 1 (for example, by using the method
5 described in the previous paragraph), then there will never
be a divide-by-zero problem with the derivative computation.

Another exemplary embodiment includes methods for
estimating important aspects of SOH without employing a full
filter 1100. The full filter 1100 method may be
10 computationally intensive. If precise values for the full
set of cell model parameters are not necessary, then other
methods potentially less complex or computationally intensive
might be used. The exemplary methodologies determine cell
capacity and resistance using filtering methods. The change
15 in capacity and resistance from the nominal "new-cell" values
give capacity fade and power fade, which are the most
commonly employed indicators of cell SOH.

In this example, to estimate cell resistance using a
filtering mechanism, we formulate a model:

$$\begin{aligned} R_{k+1} &= R_k + r_k \\ y_k &= \text{OCV}(z_k) - i_k R_k + e_k \end{aligned} \quad (33)$$

where R_k is the cell resistance and is modeled as a constant
value with a fictitious noise process r_k allowing adaptation.
 y_k is an estimate of the cell's voltage, i_k is the cell
current, and e_k models estimation error. If an estimate of z_k
25 that may be externally generated and supplied is employed,
then a filter 1100 may be applied to this model to estimate
cell resistance. In the standard filter 1100, the model's

prediction of y_k is compared with the true measured cell voltage. Any difference resultant from the comparison is used to adapt R_k .

Note that the above model may be extended to handle
 5 different values of resistance for a variety of conditions of the cell 22. For example, differences based on charge and discharge, different SOC's, and different temperatures. The scalar R_k may then be established as a vector comprising all of the resistance values being modified, and the appropriate
 10 element from the vector would be used each time step of the filter during the calculations.

In this example, to estimate cell capacity using a filter 1100, we again formulate a cell model:

$$\begin{aligned} C_{k+1} &= C_k + r_k \\ 0 &= z_k - z_{k-1} + \eta_{i,k} i_{k-1} \Delta t / C_{k-1} + e_k. \end{aligned} \quad (34)$$

15 Again, a filter is formulated using this model to produce a capacity estimate. As the filter 1100 runs, the computation in the second equation (right-hand-side) is compared to zero, and the difference is used to update the capacity estimate. Note that good estimates of the present and previous states-
 20 of-charge are desired, possibly from a filter estimating SOC. Estimated capacity may again be a function of temperature (and so forth), if desired, by employing a capacity vector, from which the appropriate element is used in each time step during calculations.

25

Industrial Applicability

Thus, a method for estimation of cell parameters has been described in conjunction with a number of specific embodiments. One or more embodiments use a Kalman filter

1100. Some embodiments use an extended Kalman filter 1100. Further, some embodiments include a mechanism to force convergence of one or more parameters. One or more embodiments include a simplified parameter filter 1100 to
5 estimate resistance, while some embodiments include a simplified parameter filter 1100 to estimate total capacity. The present invention is applicable to a broad range of applications, and cell electrochemistries.

The disclosed method may be embodied in the form of
10 computer-implemented processes and apparatuses for practicing those processes. The method can also be embodied in the form of computer program code containing instructions embodied in tangible media 52, such as floppy diskettes, CD-ROMs, hard drives, or any other computer-readable storage medium,
15 wherein, when the computer program code is loaded into and executed by a computer, the computer becomes an apparatus capable of executing the method. The present method can also be embodied in the form of computer program code, for example, whether stored in a storage medium, loaded into and/or
20 executed by a computer, or as data signal 54 transmitted whether a modulated carrier wave or not, over some transmission medium, such as over electrical wiring or cabling, through fiber optics, or via electromagnetic radiation, wherein, when the computer program code is loaded
25 into and executed by a computer, the computer becomes an apparatus capable of executing the method. When implemented on a general-purpose microprocessor, the computer program code segments configure the microprocessor to create specific logic circuits.

It will be appreciated that the use of first and second or other similar nomenclature for denoting similar items is not intended to specify or imply any particular order unless otherwise stated. Furthermore, the use of the terminology
5 "a" and "at least one" of shall each be associated with the meaning "one or more" unless specifically stated otherwise.

While the invention has been described with reference to an exemplary embodiment, it will be understood by those skilled in the art that various changes may be made and
10 equivalents may be substituted for elements thereof without departing from the scope of the invention. In addition, many modifications may be made to adapt a particular situation or material to the teachings of the invention without departing from the essential scope thereof. Therefore, it is intended
15 that the invention not be limited to the particular embodiment disclosed as the best mode contemplated for carrying out this invention, but that the invention will include all embodiments falling within the scope of the appended claims.

20

Claims

1. A method for estimating present parameters of an electrochemical cell system comprising:

5 receiving a state estimate and ;
 determining a current measurement;
 determining a voltage measurement;
 making an internal parameter prediction by using said
state estimate, said current measurement and said voltage
10 measurement in a mathematical model;

 making an uncertainty prediction of said internal
parameter prediction by using said state estimate, said
current measurement and said voltage measurement in said
mathematical model; and

15 correcting said internal parameter prediction and
said uncertainty prediction;

 applying an algorithm that iterates said making an
internal parameter prediction, said making an uncertainty
prediction and said correcting to yield an ongoing
20 estimation to said parameters and an ongoing uncertainty
to said parameters estimation.

2. The method of claim 1 wherein said correcting
comprises:

25 computing a gain factor;
 computing a corrected internal parameter prediction
using said gain factor, said voltage measurement and said
internal parameter prediction; and

 computing a corrected uncertainty prediction using
30 said gain factor and said uncertainty prediction.

3. The method of claim 2 wherein said applying comprises using said corrected internal parameter prediction and said corrected uncertainty prediction to obtain predictions for a next time step where said algorithm
5 repeats.

4. The method of claim 3 wherein said algorithm is at least one of a Kalman Filter and an extended Kalman Filter.

10

5. The method of claim 4 wherein said internal parameter includes one or more of: a resistance, a capacity, a polarization voltage time constant, a polarization voltage blending factor a hysteresis blending factor, a hysteresis
15 rate constant, and an efficiency factor.

20

6. The method of claim 1 wherein said making an uncertainty prediction further comprises determining a temperature measurement, and wherein said making an uncertainty prediction comprises using said state estimate and said current measurement, said voltage measurement, and said temperature measurement in a mathematical model.

25

7. The method of claim 1 wherein said making an internal parameter prediction further comprises:

determining a temperature measurement; and

using said state estimate, said temperature

measurement, said current measurement and said voltage measurement in a mathematical model to make said internal
30 parameter prediction.

8. The method of claim 1 wherein a filter pole is computed using a tanh function to ensure that its magnitude is less than 1.

5 9. The method of claim 1 further including an initial state value and an initial parameter value associated with the electrochemical cell.

1/13

FIG. 1

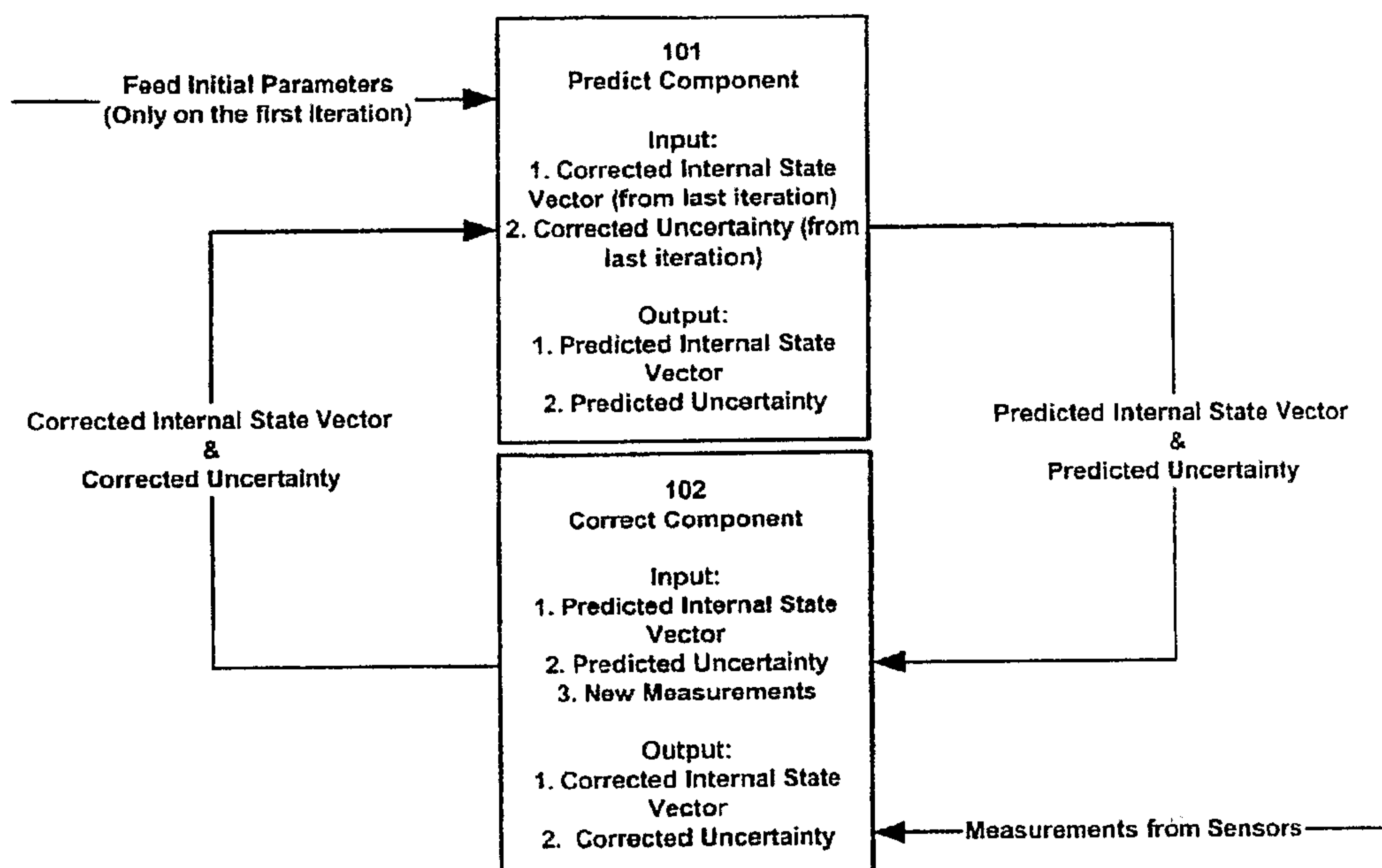
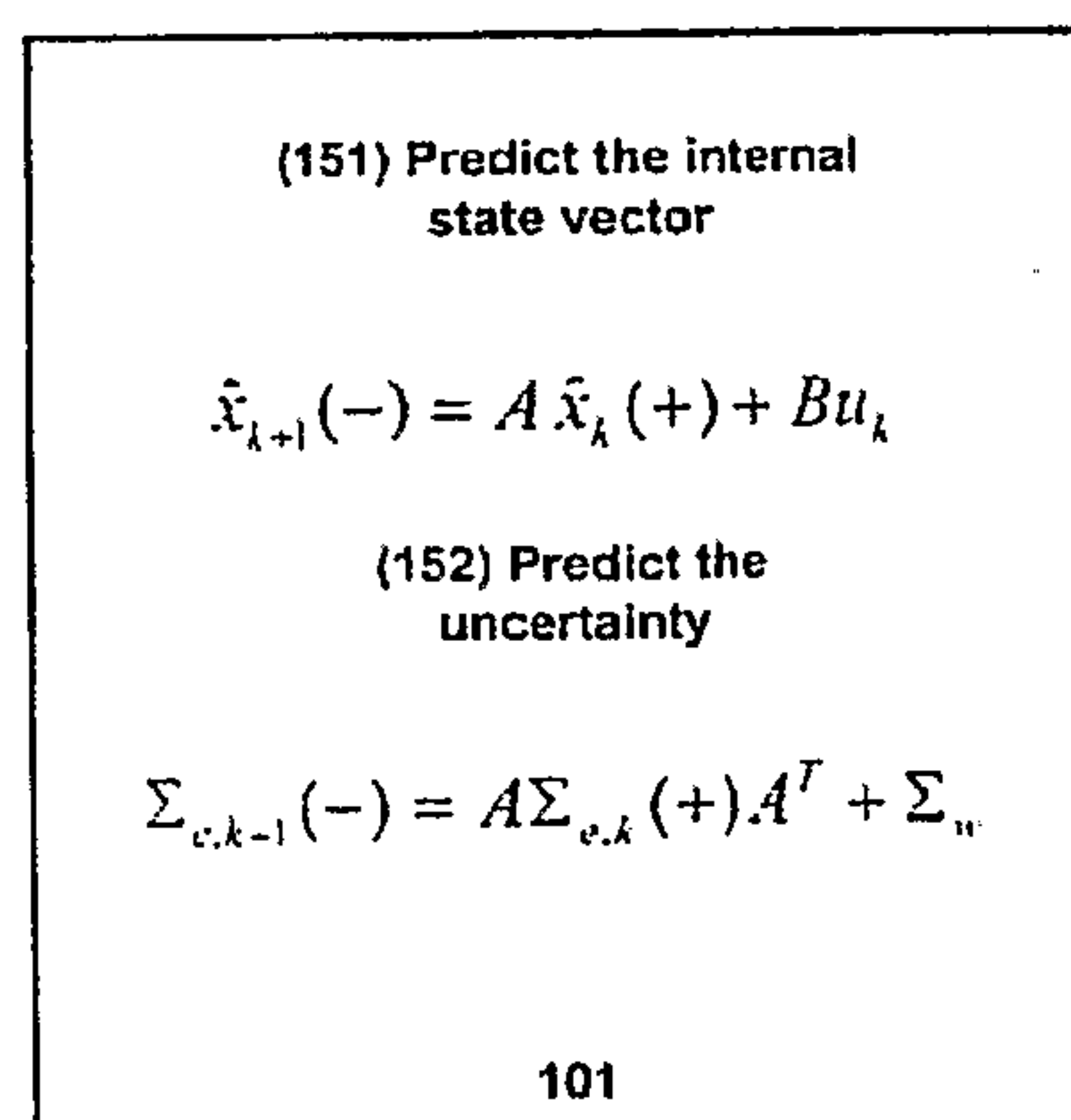


FIG. 1A



2/13

FIG. 1B

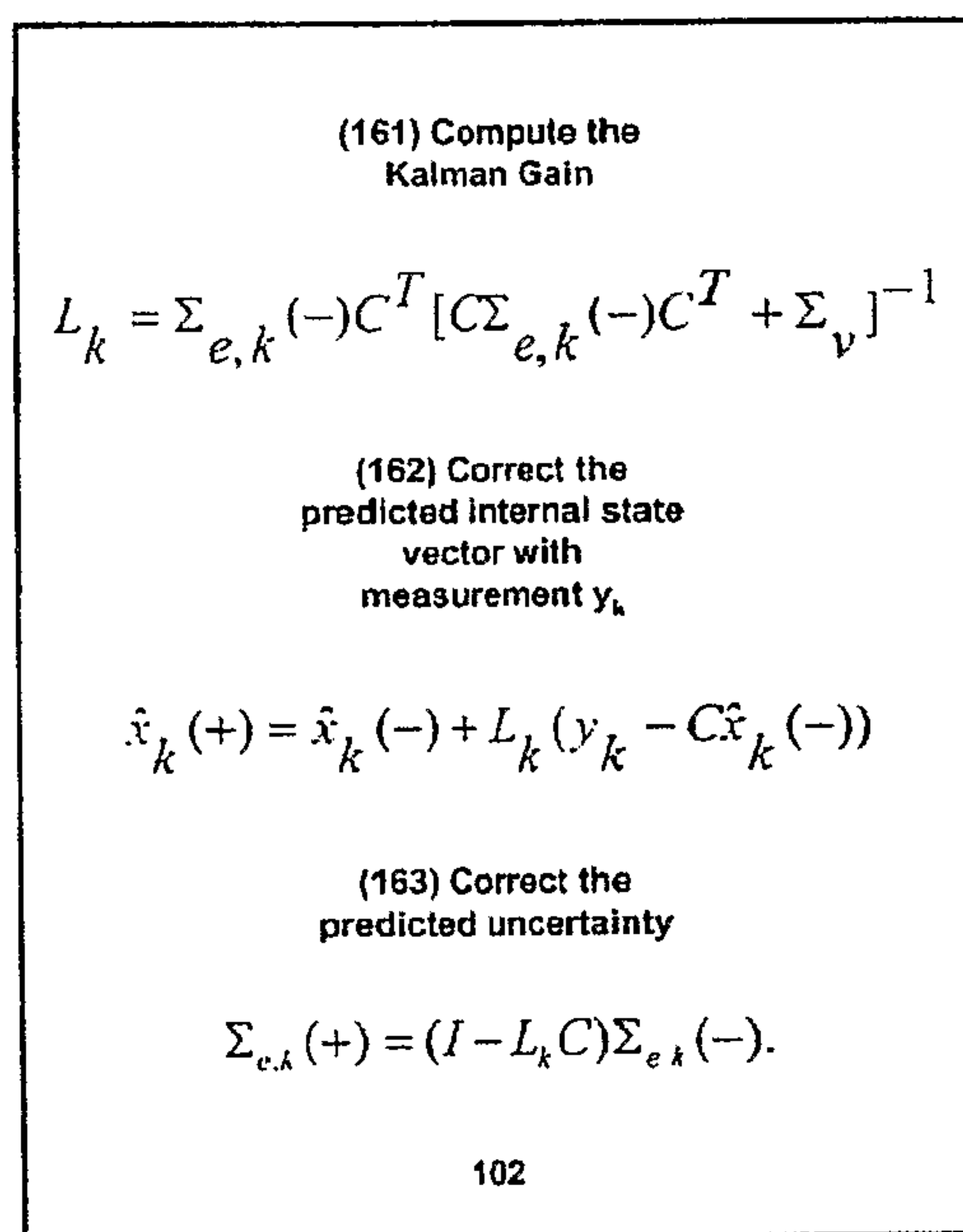
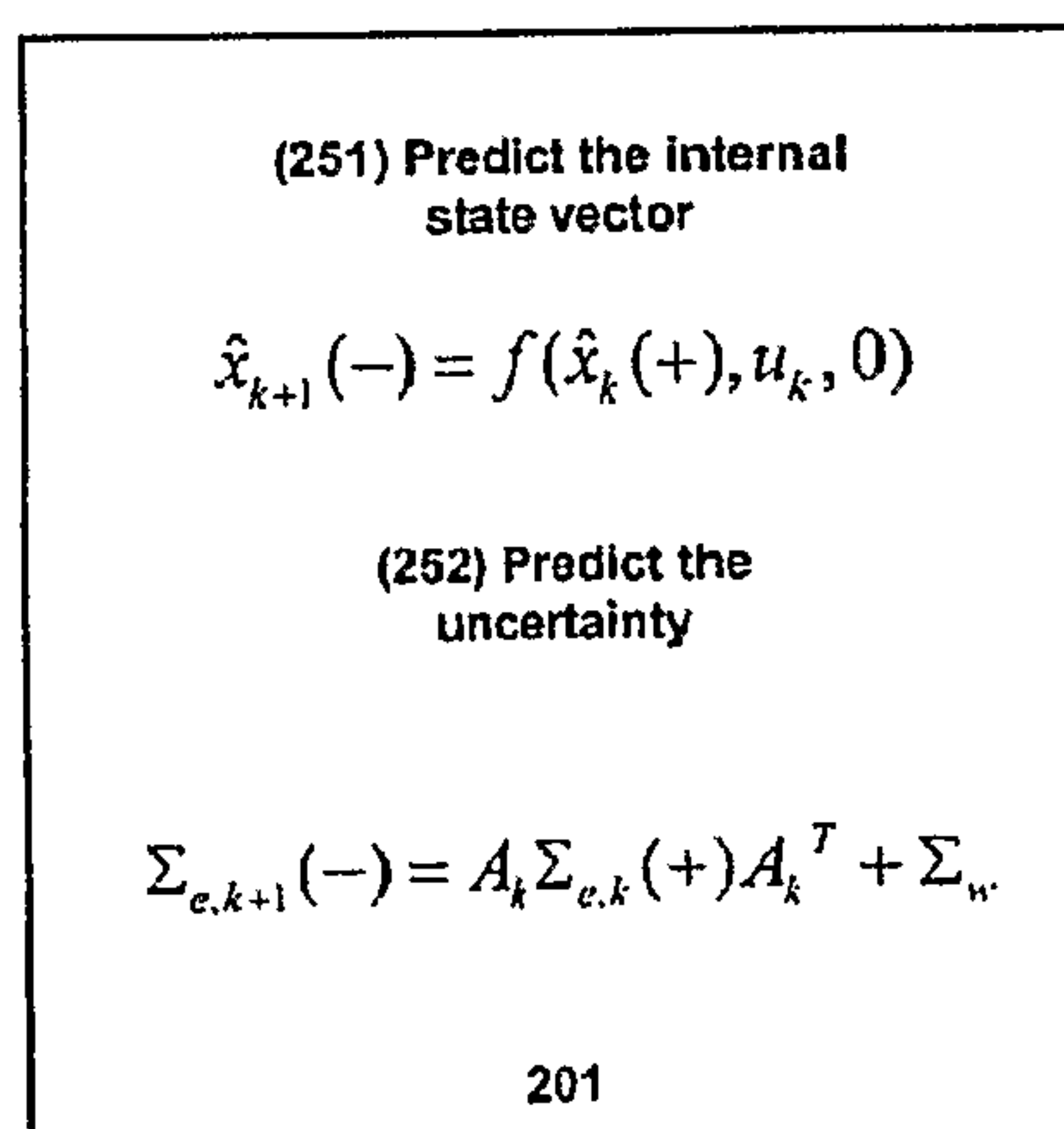


FIG. 2A



3/13

FIG. 2B

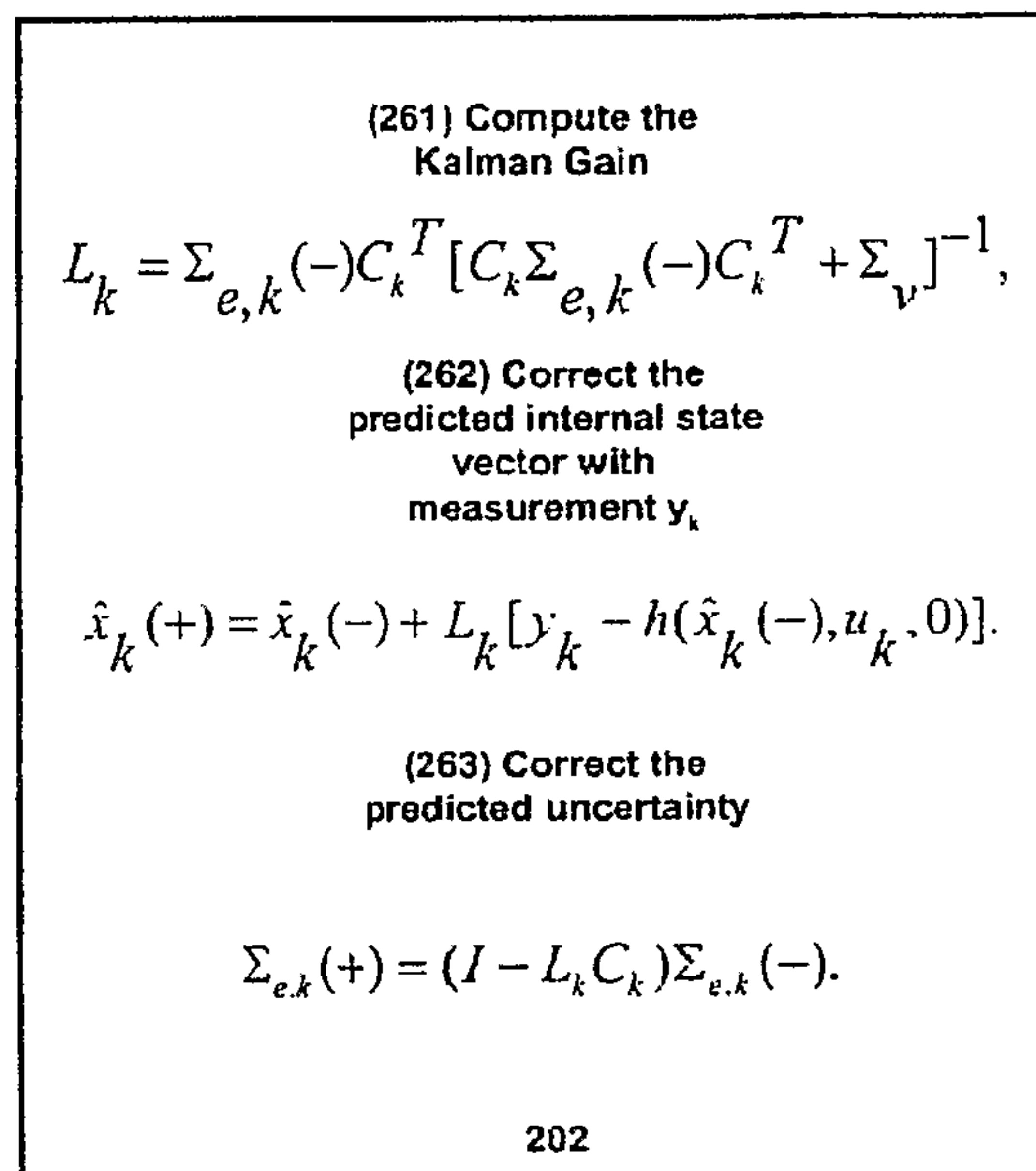
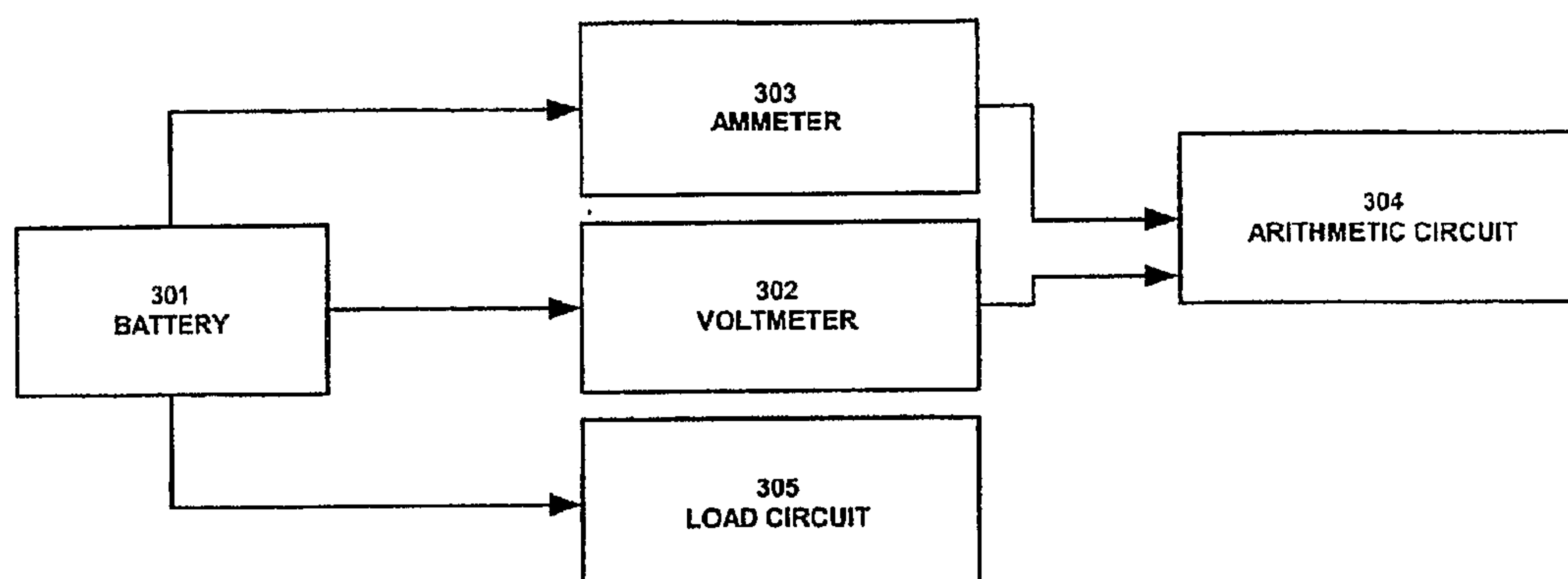


FIG. 3A



4/13

FIG. 3B

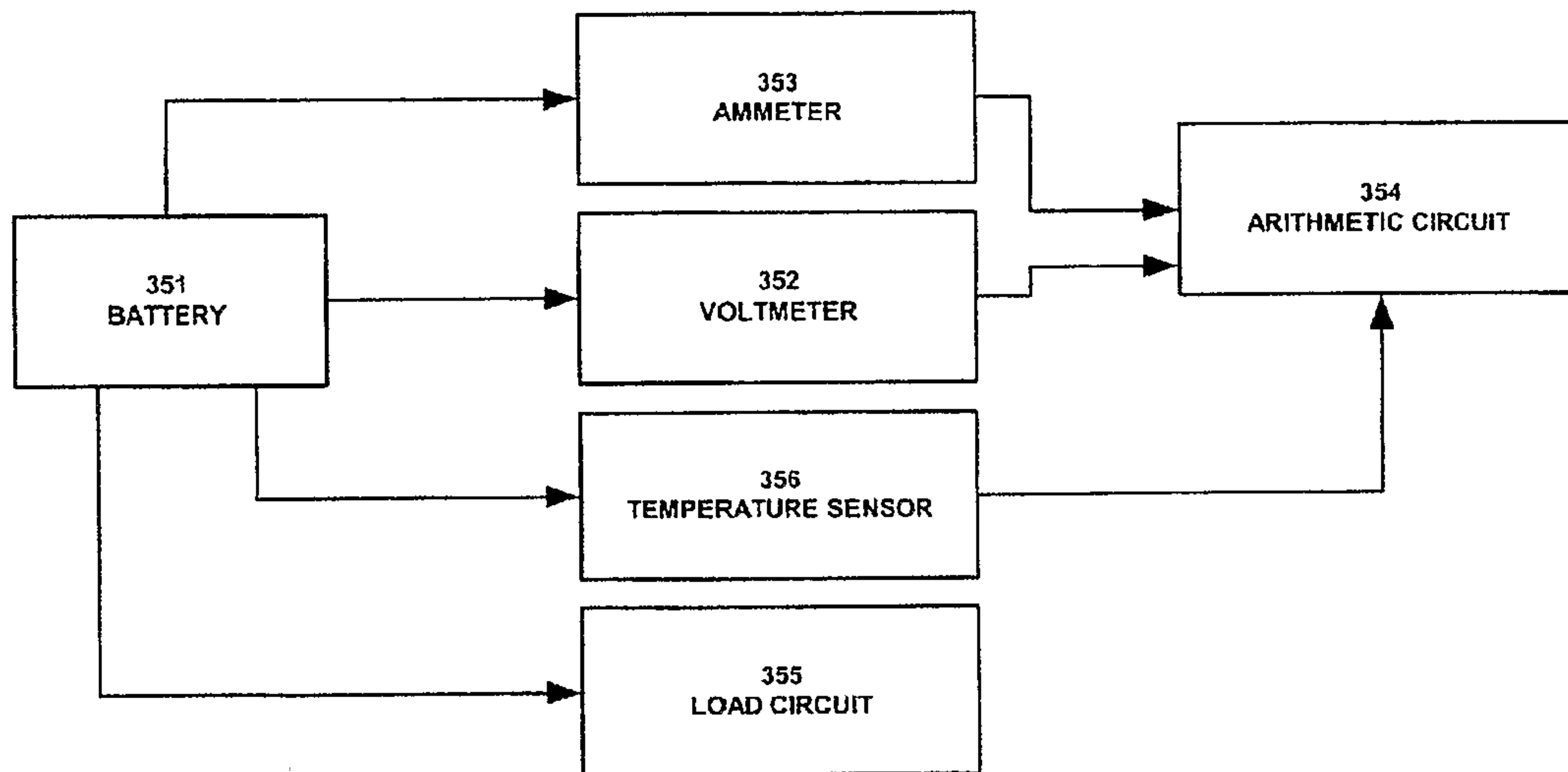
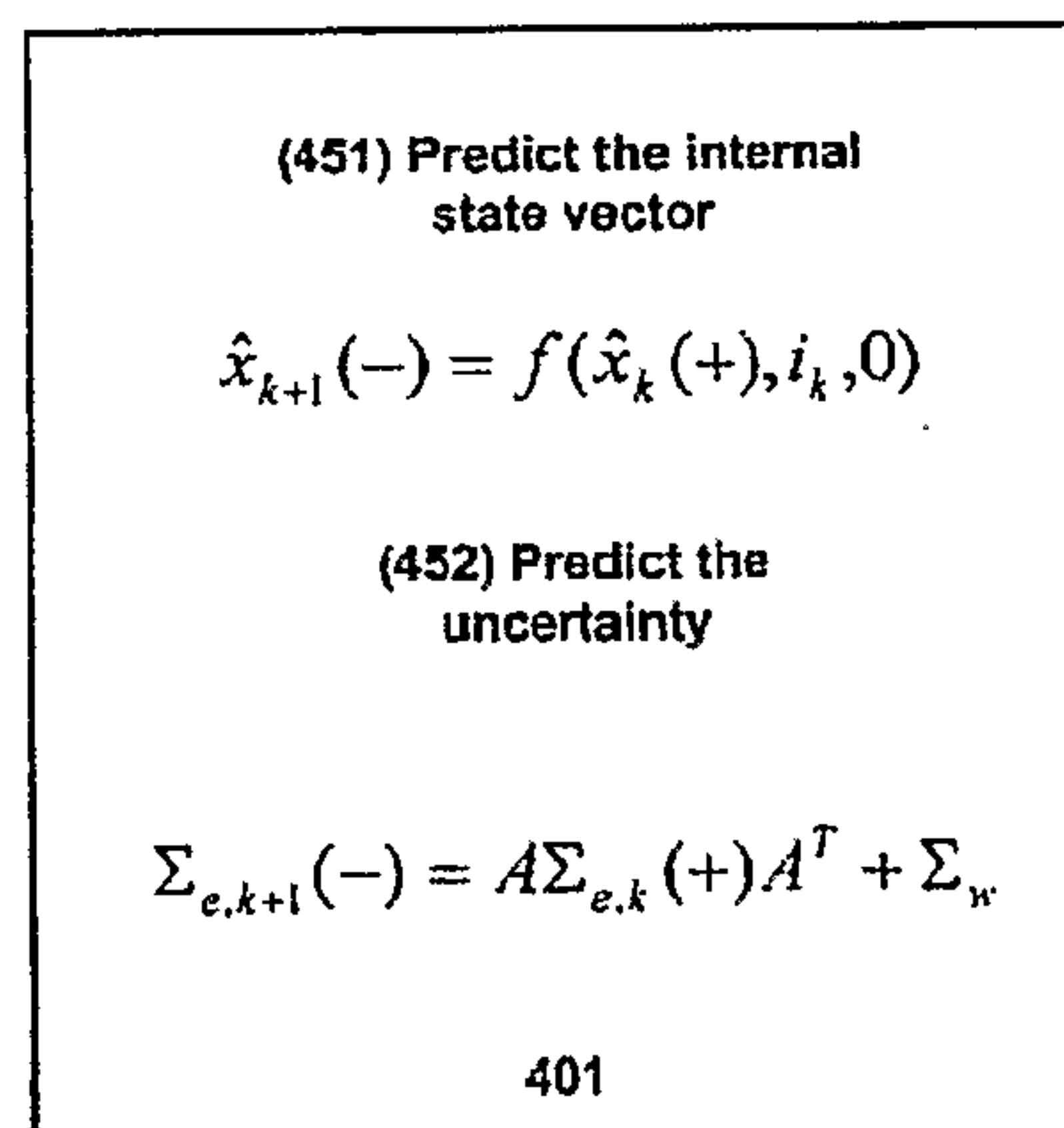


FIG. 4A



5/13

FIG. 4B

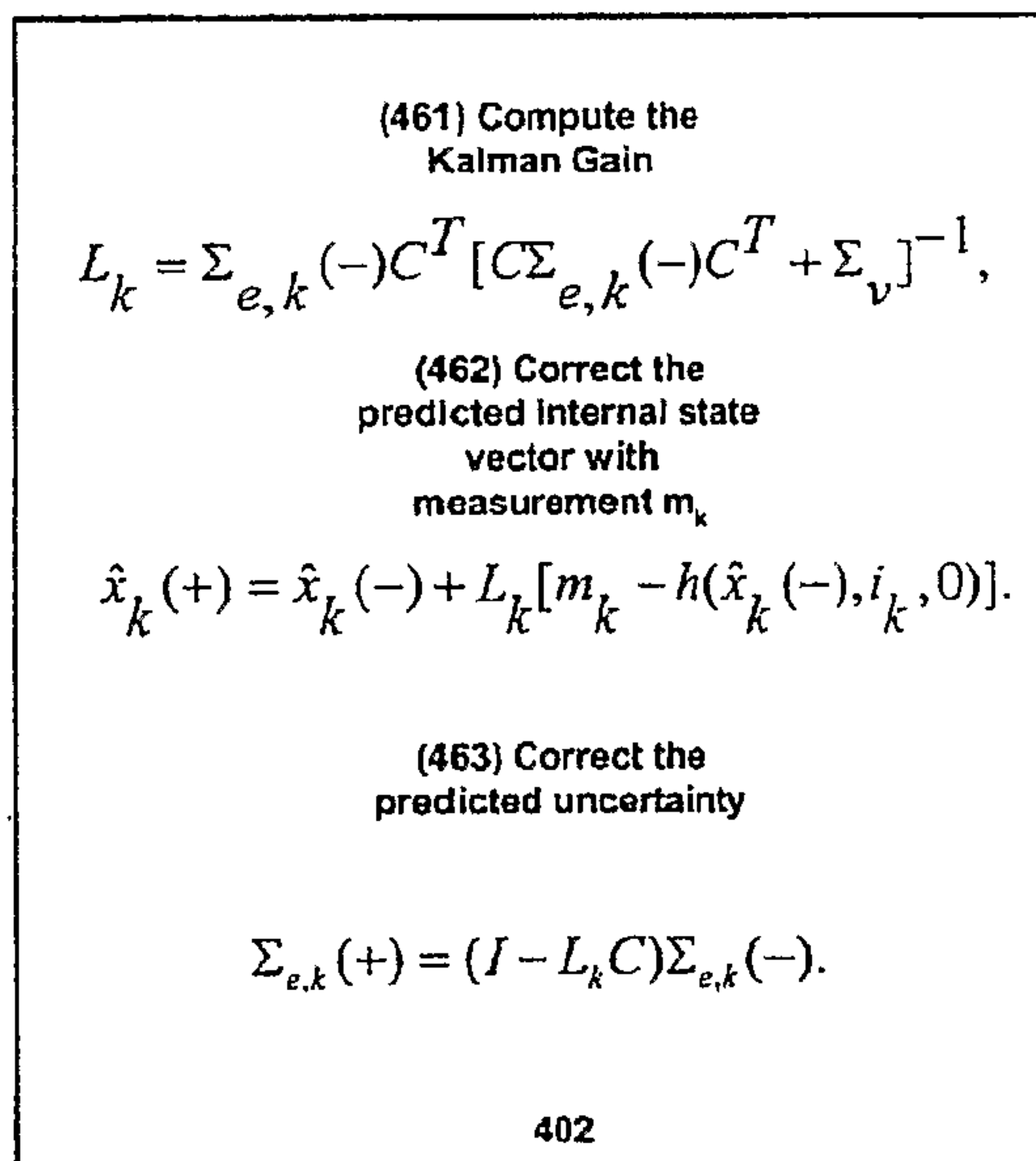
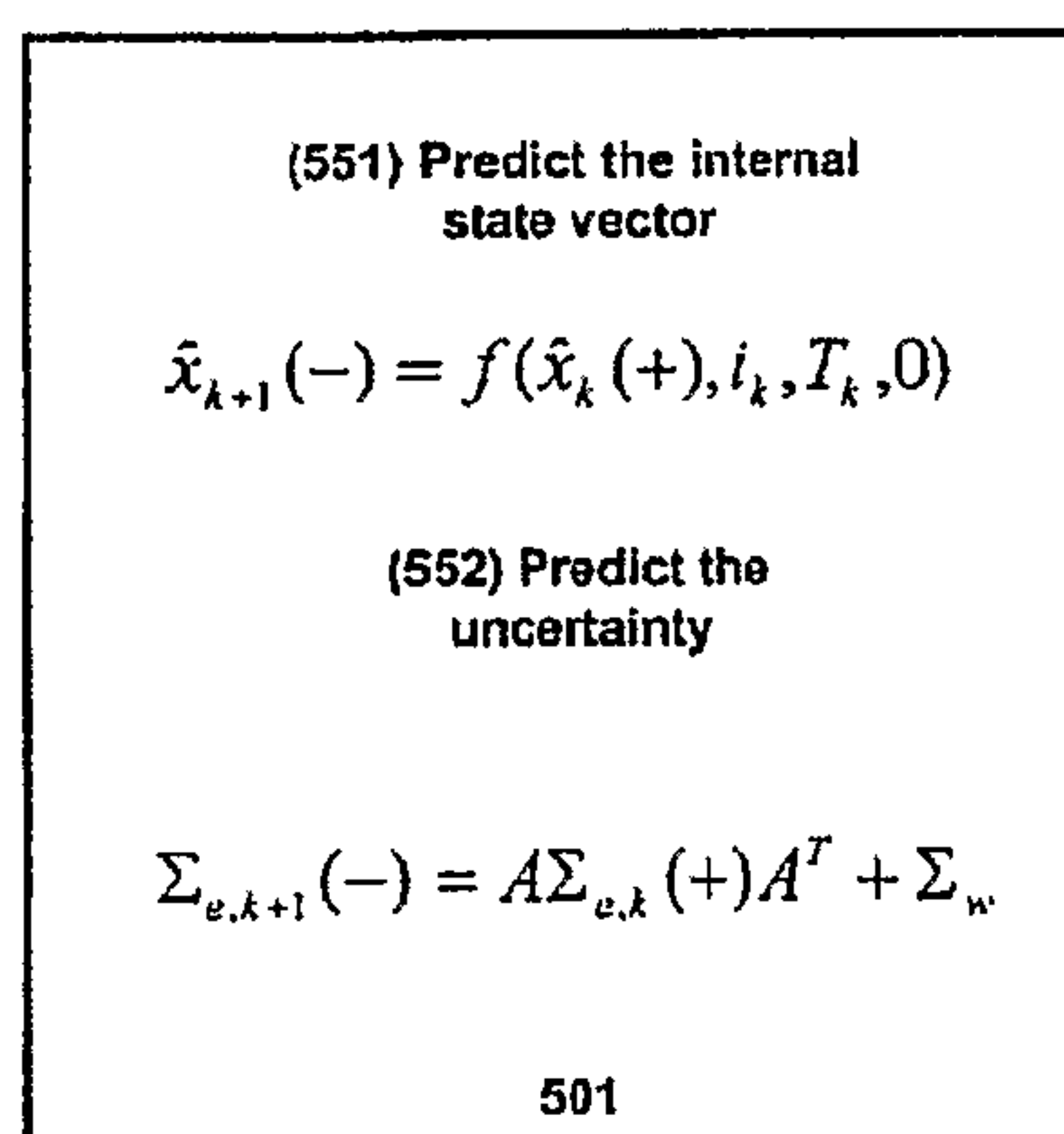


FIG. 5A



6/13

FIG. 5B

(561) Compute the
Kalman Gain

$$L_k = \Sigma_{e,k}(-)C^T [C\Sigma_{e,k}(-)C^T + \Sigma_v]^{-1},$$

(562) Correct the
predicted internal state
vector with
measurement m_k

$$\hat{x}_k(+) = \hat{x}_k(-) + L_k[m_k - h(\hat{x}_k(-), i_k, T_k, 0)].$$

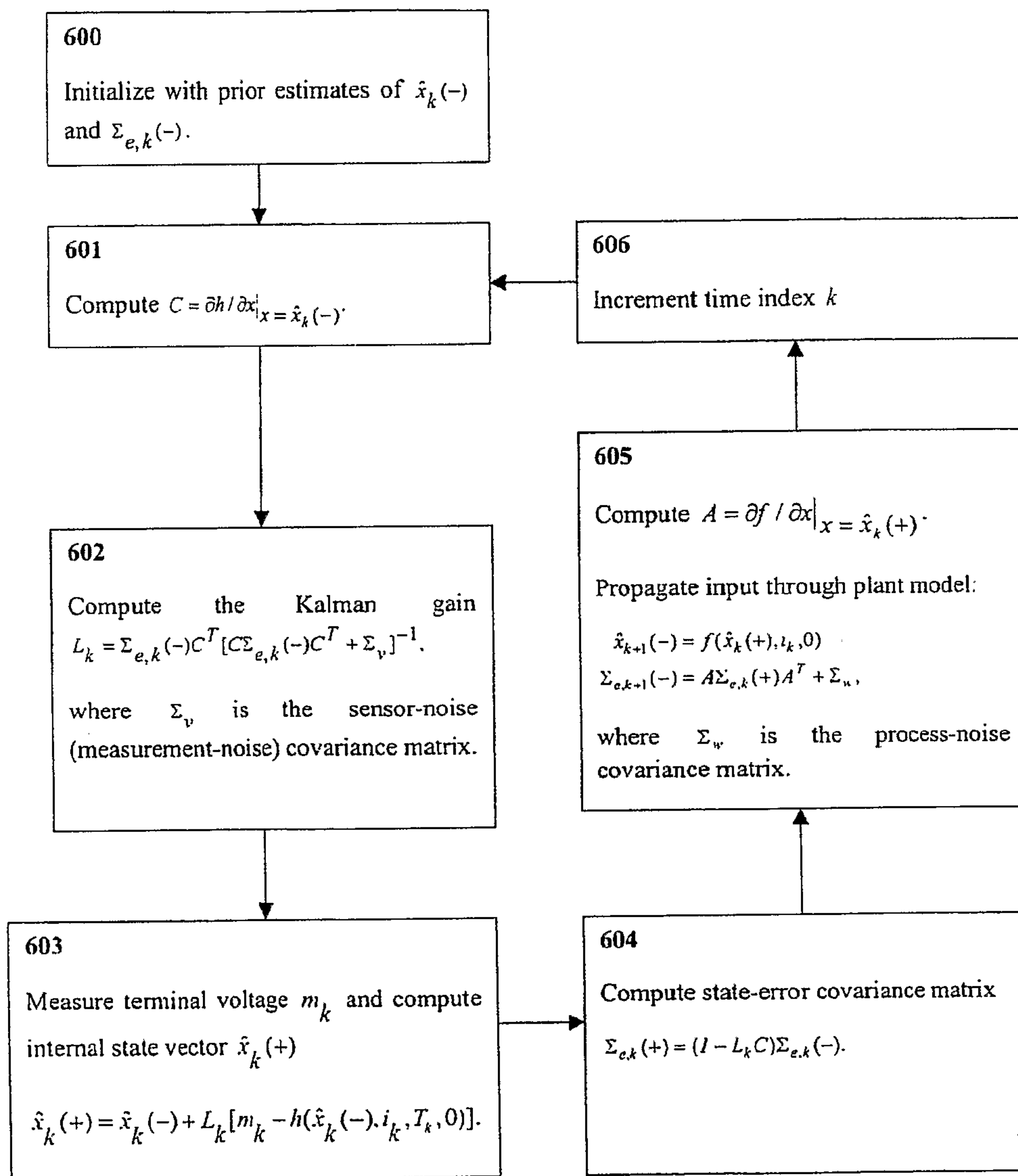
(563) Correct the
predicted uncertainty

$$\Sigma_{e,k}(+) = (I - L_k C)\Sigma_{e,k}(-).$$

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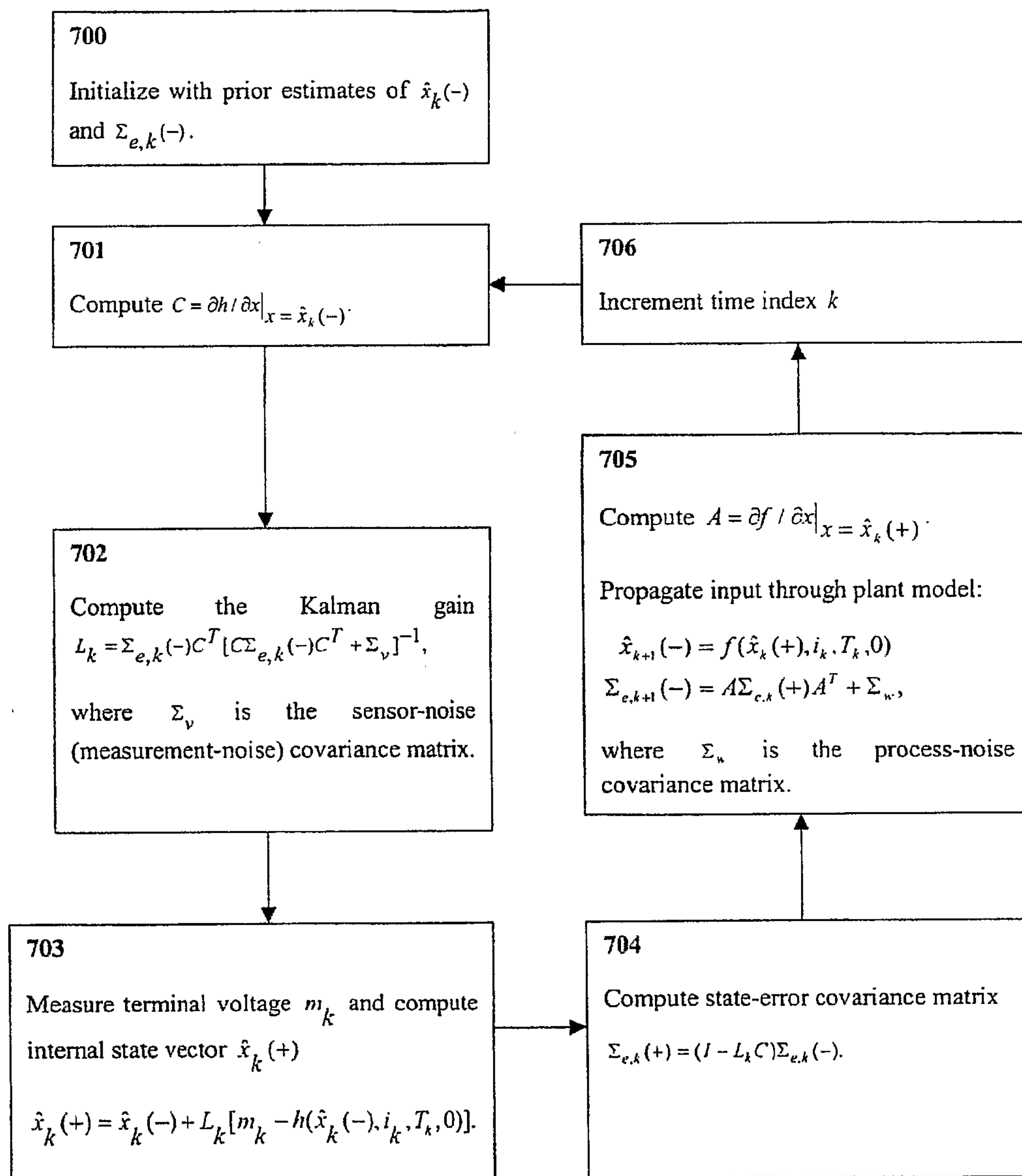
7/13

FIG. 6



8/13

FIG. 7



9/13

FIG. 8A

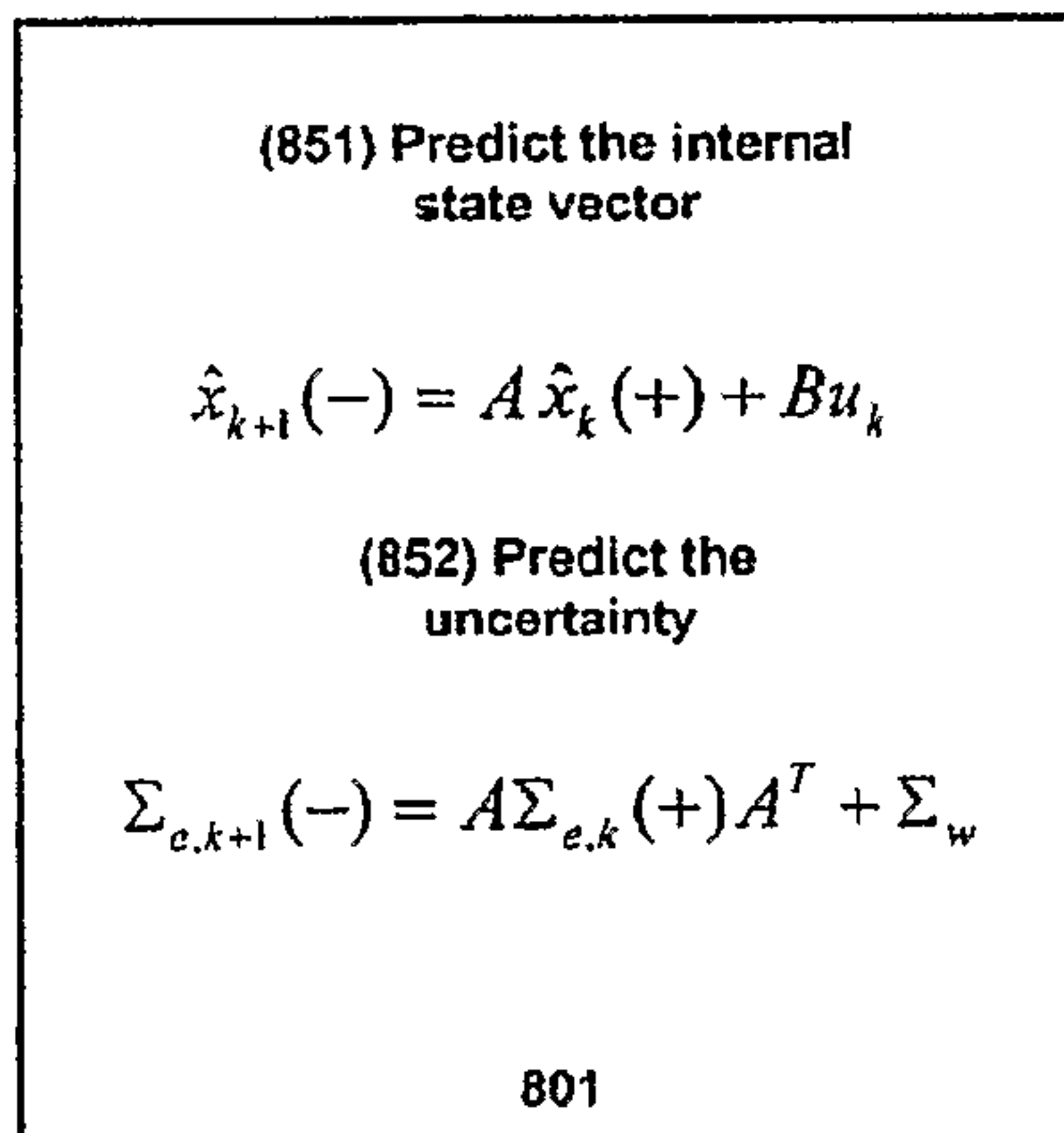
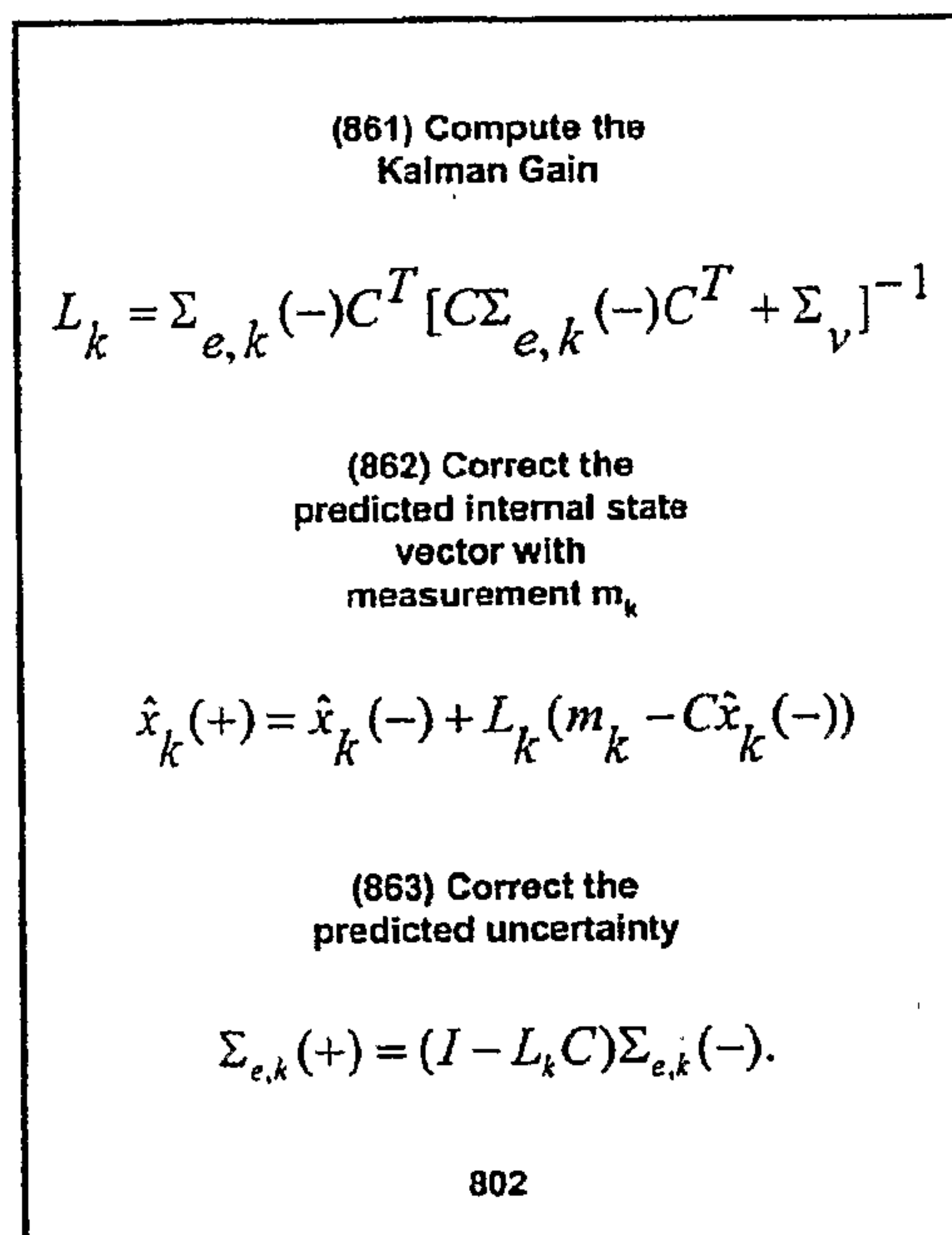
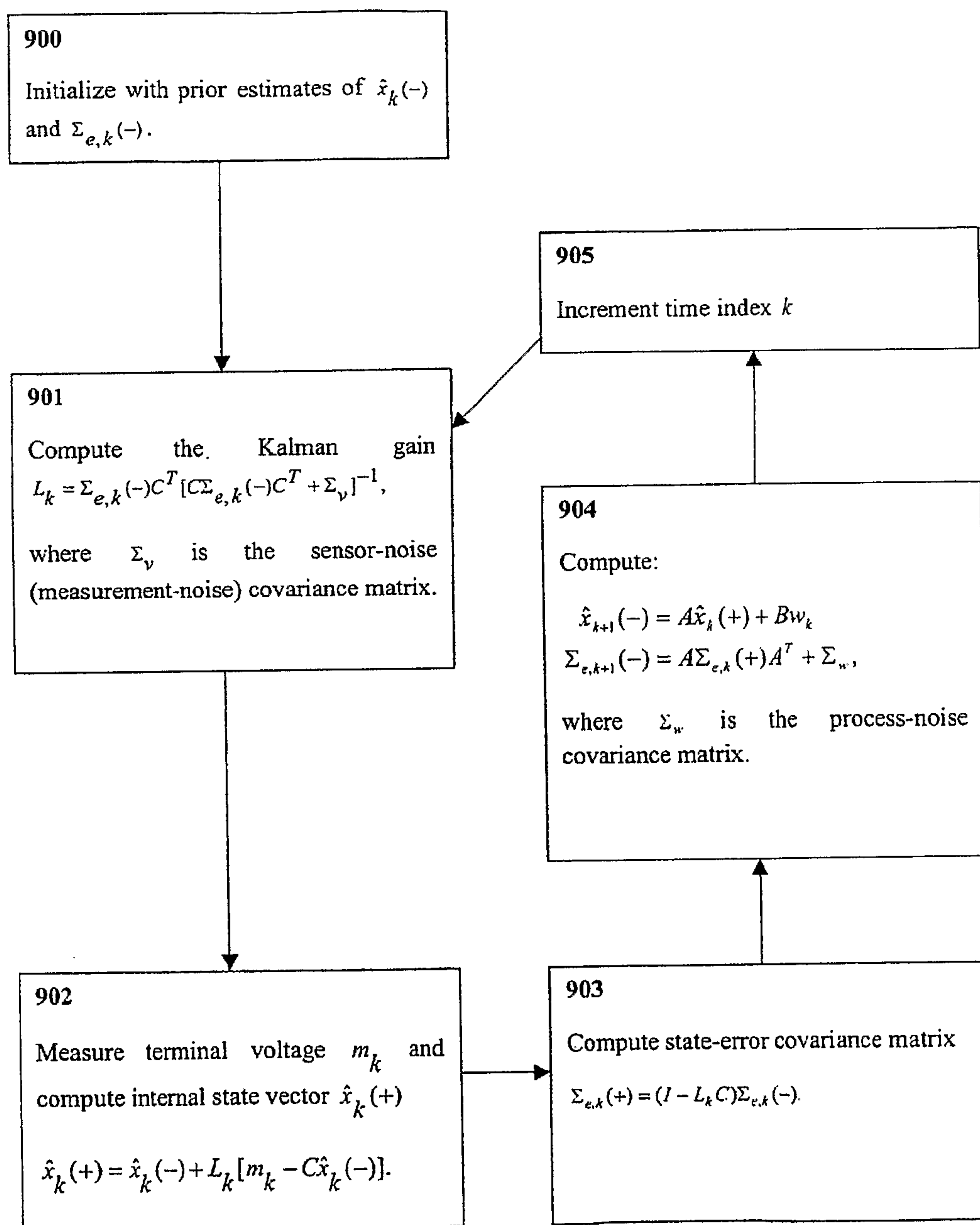


FIG. 8B



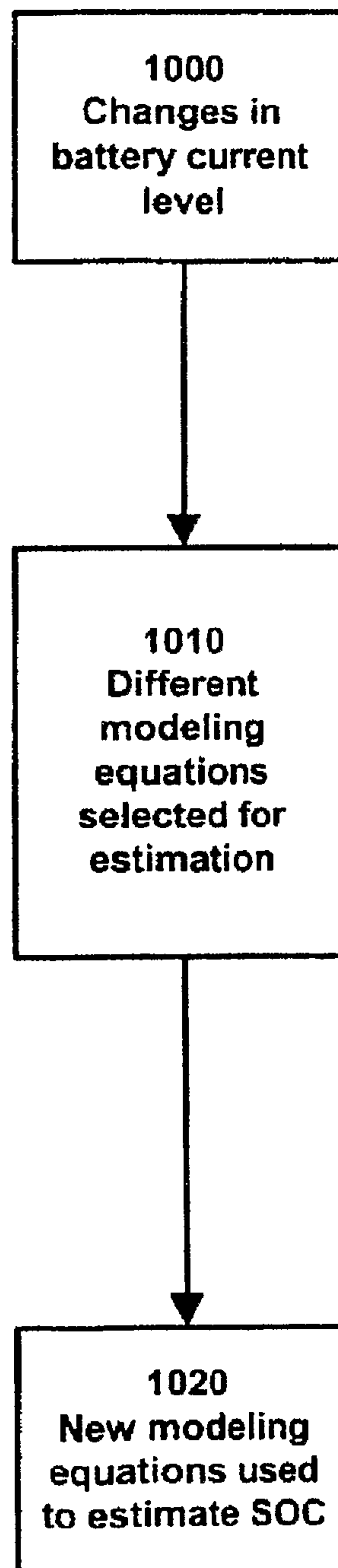
10/13

FIG. 9



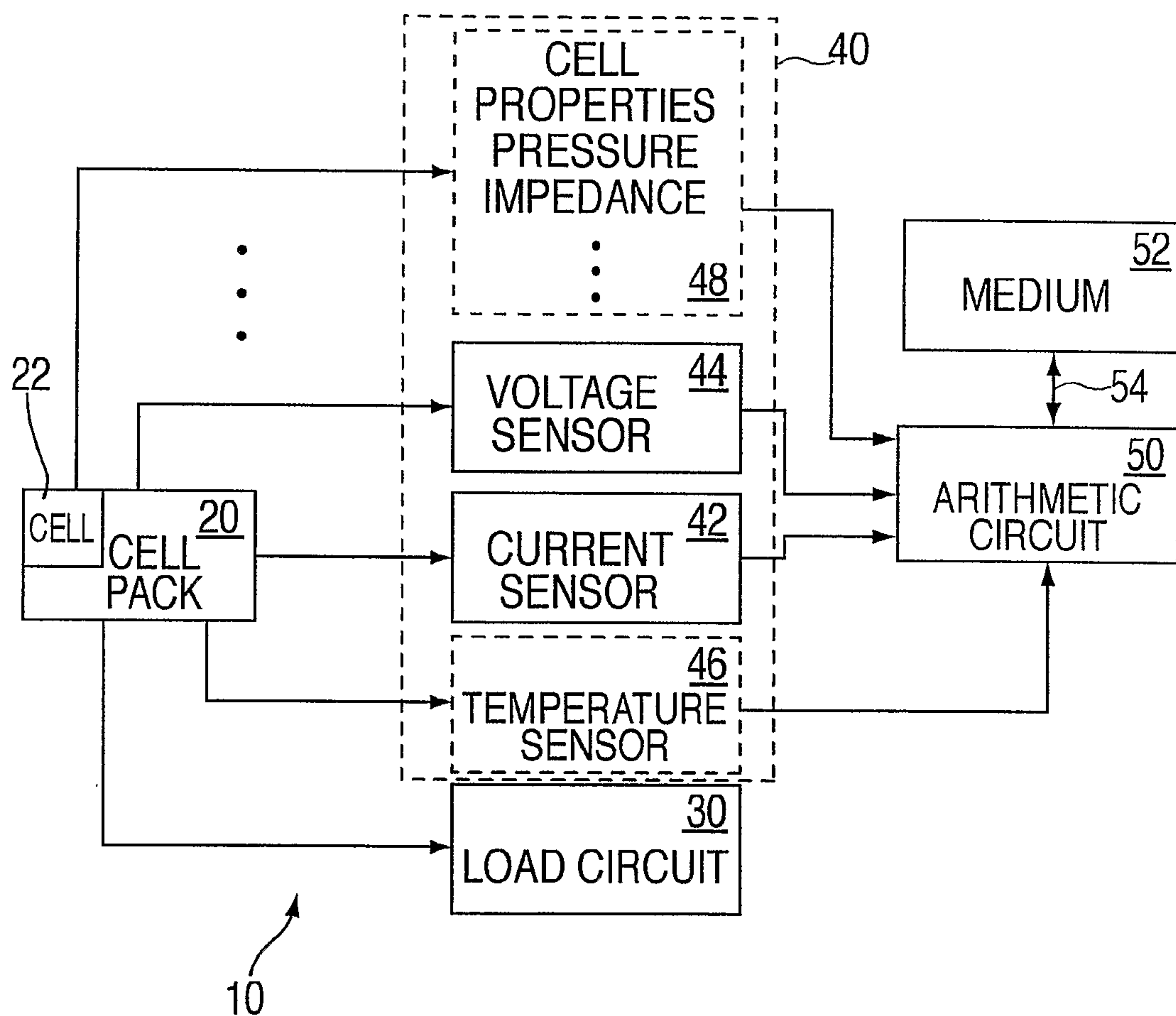
11/13

FIG. 10



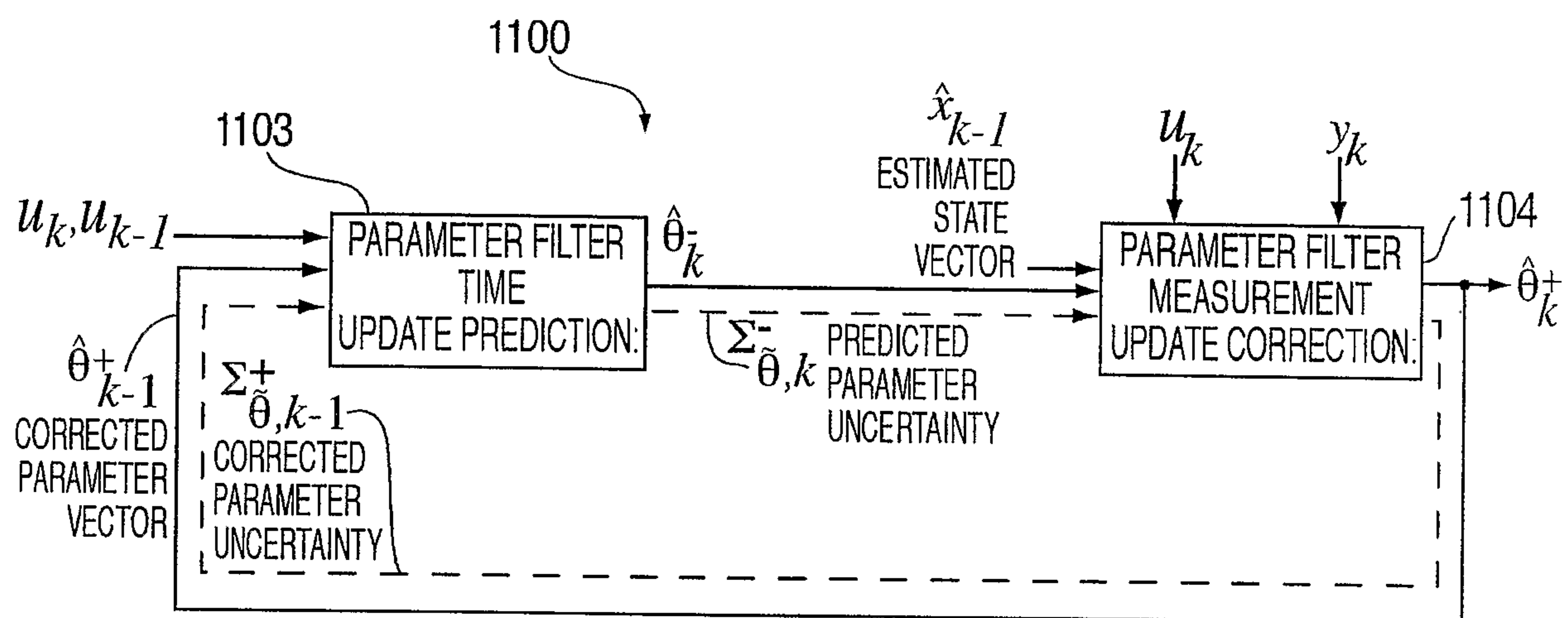
12/13

FIG. 11

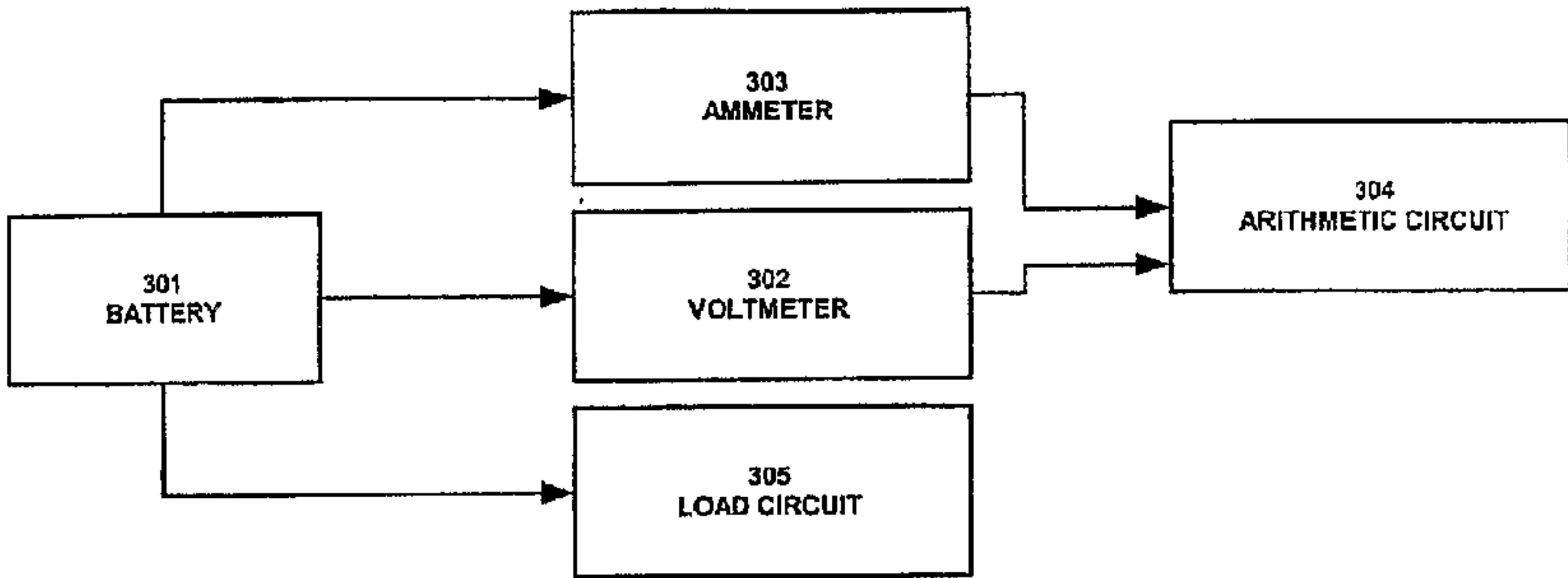


13/13

FIG. 12



A



B

