Multiple-Model Adaptive Estimation of a Hydraulic Wind Power System

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Abstract—Nonlinear model of hydraulic wind power system operates on a wide spectrum of operating points such as random wind speed disturbances and applied control commands. Thus, one way to linearize this model is to use multiple linear models representing the whole range of operating points. This paper introduces a minimal number of fixed linear models in a multiple model adaptive estimation (MMAE) framework to reduce the state estimation error. System parameters such as pressures of the pump and motors can be estimated while the overall error in entire operating points is reduced. The algorithm is composed of a bank of Kalman filters, each of which is modeled to match particular real world operating condition. Simulation results demonstrate that the adaptive approach can optimally estimate the state variables in a wide range of operating points.

I. INTRODUCTION

Recently, Wind Power systems are considerably growing due to the exhaustion and the environmental concerns of hydrocarbons. Advancements in wind turbine manufacturing reduced production costs such that wind turbines can now become a major source of power for the world’s demands [1]. In the conventional wind turbines, the horizontal axis wind turbine (HAWT), the rotor converts the wind energy into rotating shaft. This rotor is connected to a drive train, gearbox, and electric generator, which are integrated in a nacelle located at the top of towers. These components, specifically the variable speed gearbox, are expensive, bulky, and require regular maintenance, which keeps wind energy production expensive. In addition, because the gearbox and generator are located at such a height, high maintenance expenses are incurred [2].

Hydraulic wind power systems are new types for wind power harvesting which offer several advantages over geared power transfer system counterparts. In this method, the gearbox is replaced with a hydraulic pump, which is coupled with the wind turbine to generate high-pressure hydraulic fluid in the system. This flow can be used to drive a number of generators shown in Fig. 1. When controlled, the hydraulic flow is distributed between two hydraulic motors coupled with electric generators to supply electric power to the grid. The intermittent nature of wind speed results in the fluctuation on the wind turbine generator angular velocity [3], [4] and the power generation. To mitigate the effect of the output power fluctuations, an advanced control technique must be considered for the speed regulation of the generation units [5].

Nevertheless, the speed control of hydraulic wind power systems is challenging, since it is a nonlinear system under random disturbance inputs i.e. wind speed. The Nonlinearities in such systems are originated from nonlinear behavior of components such as check valves, directional valves and more importantly the proportional valve. These nonlinearities will cause behavioral changes and variations in the system. Therefore, the speed control of the system would require an in-depth modeling. The controller’s performance depends on states variables while the system is influenced by large input variations in a wide operating range.

Fig. 1. Schematic of the high-pressure hydraulic power transfer system. The hydraulic pump is in a distance from the central generation unit.

The design of a single state observer for a given plant requires exact knowledge of the plant parameters and the disturbances on the system for superior performance. In practice, parameter uncertainty and disturbances will impact the performance and robustness of the observer. In fact, incorrect modeling in the observer design may lead to large estimation errors or even error divergence.

To mitigate this problem, adaptive estimation algorithms (where the adaptation is with respect to the disturbances and uncertainty in the plant parameters) have been proposed in the literature such as Newton-type adaptive estimation algorithms [6], and least squares adaptive algorithms [7]. Among these, the Multiple-Model Adaptive Estimation (MMAE) algorithm has received particular attention because of its functionality with respect to uncertainties and wide operating-regime systems [8], [9]. However, the use of multiple models for adaptive estimation refers back to the 1960s and 1970s when several authors studied Kalman filter based estimators. Kalman filter offers some advantageous such as its
convenience form for online real time processing, ease of
system formulation and implementation, and superior
implementation performance [10].

Throughout past decade, a number of papers have made
efforts to describe the use of multiple- model architectures for
adaptive estimation and control, e.g. [11], [12], and [13].
While some have employed deterministic continuous-time
methodologies [14], others utilized a discrete-time probabilistic
approach [15]. All of these papers utilize multiple-model
architecture for the identification system. Multiple-model
adaptive estimation (MMAE) was first proposed by Magill [16]
and has been used in several papers obtaining numerous results
on its properties such as state observers [17].

In the stochastic version of the MMAE [18], a separate
discrete-time Kalman filter (KF) is developed for each selected
model defined by a hypothesized parameter and disturbance
vector in a wide range of system operating points. The
resulting set of KFs forms a “bank” where each local KF
generates its own state estimate and an output error (residual).
The bank of KFs runs in parallel and at each sampling instant,
the MMAE uses the measurement residuals to compute the
conditional probability \( p \). The higher probability will
correspond the plant to a true plant model. The state estimation
is a probabilistically weighted combination of all KF estimates.
The rationale is that the highest probability should be assigned
to the state estimation provided by the most accurate KF, and
lower probabilities assigned to the remaining KFs [10], [19].

In this paper, MMAE is utilized for state estimation of a
nonlinear hydraulic wind power system. The system is
subject to multiple operating regimes which are initiated by
external factors such as changes in control command or
persistent plant disturbances (e.g., variations in wind speed).

In the next section, the modeling of hydraulic wind power
will be introduced. Linear modeling of the system in different
operating point will be explained in section III. Section IV
discusses the Kalman filter and MMAE framework. Finally,
the main results will be analyzed in section V.

II. HYDRAULIC WIND POWER SYSTEM MODEL

To derive the state space representation of the hydraulic
wind power system, the integrated configuration of the
hydraulic components must be considered. References [20] and
[21] introduce nonlinear model of hydraulic circuit
components, and provides a nonlinear state space representation of the hydraulic wind energy transfer. The key
advantages of the state space representation comprise of
detailed mathematical demonstration of the system that
incorporates initial conditions into solution, and represents the
interrelation of the system equations, suitability for multiple
input-multiple output (MIMO) system illustration, and superior
computational efficiency for computer implementation.

In general, the nonlinear state space model of a system can be
represented as

\[
\dot{x} = f(x) + g(x)U
\]

\[
y = h(x),
\]

where \( x \) is the state vector, \( y \) is the output vector, \( U \) is the input
vector, \( f(x) \) is an input independent function vector of the
states, \( g(x) \) is the input dependent function matrix of the state
variables, and \( h(x) \) is the output function. The state space
model is achieved in [21] with states and inputs as follows:

\[
x = \begin{bmatrix} P_p & P_{ma} & P_{mb} & \omega_{ma} & \omega_{mb} \end{bmatrix}^T, \quad U = \begin{bmatrix} h \end{bmatrix},
\]

where the inputs to the hydraulic system are \( \omega_p \), the angular
velocity of the hydraulic pump (wind speed), and \( h \),
the position of the proportional valve. The state variables are the
pressure of the pump \( (P_p) \), pressure of the Motor A \( (P_{ma}) \),
pressure of the motor B \( (P_{mb}) \), the primary motor angular
velocity \( (\omega_{ma}) \), and the auxiliary motor angular velocity
\( (\omega_{mb}) \).

III. MULTIPLE-MODEL LINEARIZATION

The linearization of nonlinear systems provides
approximation of the dynamical behavior within a range of
variables and operating conditions. Then, well-developed linear
models can be used to analyze the system behavior or to
control the original nonlinear systems.

However, the results of analysis of nonlinear systems using
linearized models should be carefully interpreted in order to
avoid unacceptably large errors due to the approximation in the
linearization process [22]. The linearization technique used in
this paper is to utilize a local linear model for each of the
different plant’s operating conditions. Multiple linearized
models are therefore developed to cover the entire operating
conditions. Each model should satisfactorily describe the plant
in a region around a specific operating point. This linearized
plant will have an effective range of linearization, in which the
system generates limited deviation from the original plant. Out
of this range, the linearized plant’s performance is reduced
hence new plants with shifted operating conditions are
required. The regions that fall into effective range of several
plants may be approximated by a weighting factor associated
with each model involved. An average of all models will
present the system. By doing this, any linear estimation
technique may be used to combine the information contained in
the local model into a global description of the plant, and then
carrying out state estimation by tracking transition on-line to
provide a means to control the system [23], [24].

Nonlinear model of hydraulic wind power system operates
in a wide range of operating conditions. Thus, there would be a
need for multiple linear models to represent the whole system.
Considering the sensitivity of the system to the parameters and
inputs, it is seen that the valve position input and the wind
speed disturbance input have a great influence on the behavior
of the system. Therefore, the nonlinear system must be
linearized in different operating points specified by different control input (valve position) and disturbance input (wind speed) to describe the whole nonlinear system.

The operating points of the hydraulic wind power plant include wind speed from 200 to 600 rpm, and valve position from 0 to 0.5. This region includes an infinite number of operating points. However, many of these points can be modeled with reasonable error through a linear model. Dividing this region into 6 models, a limited error was achieved where at maximum deviation reached 7%. Fig. 2 illustrates different operating points of hydraulic wind power transfer system and selected operating point at which the nonlinear system was linearized. In this figure, each model is covering a specific area that is shown by different symbols. It can be seen that some points are covered by two or more models. Fig. 3 demonstrates the maximum deviation of the nonlinear system outputs with that of the 6 linearized models. As the figure shows, there are some overlap among areas of each model and not all operating points have been covered with these models.

IV. THEORY OVERVIEW

A. Kalman Filter

Kalman filters are used to estimate the states of linear systems. However, if inaccurate model parameters are used to construct the filter, the state estimate accuracy will degrade and may even diverge [25]. Consider a Kalman filter model associated with a particular hypothesized status of the hydraulic wind power transfer, which is denoted with the subscript $k$. Thus, the $k$th model can be represented by [26]:

$$
\begin{align*}
    x_k(t_i) &= \Phi_k x_k(t_{i-1}) + B_k u(t_{i-1}) + G_k \omega_k(t_{i-1}) \\
    z_k(t_i) &= H_k x_k(t_i) + v_k(t_i),
\end{align*}
$$

where $x_k$ is the Kalman filter model state vector, $\Phi_k$ is the state transition matrix, $B_k$ is the control input matrix, $u$ is the system input vector, $G_k$ is the system noise matrix, $z_k$ is the measurement noise, $H_k$ is the output matrix, $\omega_k$ is an additive white discrete-time system noise with zero mean value and covariance $Q_k$ as follows:

$$
E\{\omega_k(t_i)\omega_k^T(t_j)\} = \begin{cases} Q_k, & t_i = t_j \\ 0, & t_i \neq t_j \end{cases},
$$

and $v_k$ is an additive white measurement noise that is used in the Kalman filter model. This noise is independent from $\omega_k$, with zero mean value and covariance $R_k$ as follows:

$$
E\{v_k(t_i)v_k^T(t_j)\} = \begin{cases} R_k, & t_i = t_j \\ 0, & t_i \neq t_j \end{cases}.
$$

In the hydraulic wind power system, the noise parameters $Q$ and $R$ are not accurately known, and can also change over time depending on operating conditions. To derive these noise covariance matrices, the algorithm in [27] has been used and implemented in the Kalman filter.

The Kalman filter algorithm utilizes a discrete linearized model follows:

$$
\begin{align*}
    \dot{x}_k(t_i) &= \Phi_k x_k(t_{i-1}) + B_k u(t_{i-1}) \\
    \dot{z}_k(t_i) &= H_k x_k(t_i),
\end{align*}
$$

Working on different operating points caused by control input and disturbance on the system, it is of high importance to create smooth transition among linearized models, eliminate parameter uncertainty effects, maximize the operating point coverage and minimize the estimation error in entire operating condition. As mentioned earlier, poor transition may lead to long periods of transient operation, usually accompanied by loss of information and instability.
where $\hat{x}_k$ is state estimation vector, $\hat{x}_k(t_i^*)$ is the output estimation at time $t_i^*$ of the $i$th time sample, $t_i^*$ is the time after the measurement update at the $(i-1)$th time sample, and the state estimation covariance matrix propagation is

$$P_k(t_i^*) = \Phi_k^T P_k(t_{i-1}) \Phi_k + G_k^T Q_k G_k.$$  

(7)

The state estimation will be updated using:

$$\hat{x}_k(t_i^*) = \hat{x}_k(t_i^*) + K_i(t_i^*) r_i(t_i^*),$$

(8)

where the Kalman gain is

$$K_i(t_i^*) = P_i(t_i^*) H_i^T A_i(t_i^*)^{-1},$$

(9)

and the Kalman filter-computed residual covariance matrix $A_k$ is

$$A_k(t_i) = H_i P_i(t_i^*) H_i^T + R_k.$$  

(10)

The Kalman filter residual vector, shown in (6), is defined as

$$r_i(t_i^*) = z(t_i) - H_i \hat{x}_k(t_i^*) = z_i(t_i^*) - H_i \hat{x}_k(t_i^*),$$

(11)

The covariance matrix is updated using as follows

$$P_i(t_i^*) = P_i(t_i^*) - K_i(t_i) H_i P_i(t_i^*),$$

(12)

$$\hat{x}_k(t_i^*) = \Phi_k \hat{x}_k(t_i^*)^* + B_k u(t_i^*).$$

(13)

Therefore, the steady state Kalman filter can be represented as

$$\hat{x}_k(t_i^*) = \hat{x}_k(t_i^*) + K_i r_i(t_i^*),$$

(14)

**B. Multiple-Model Adaptive Estimation (MMAE)**

A block diagram of the MMAE scheme is shown in Fig. 4. The input and output data of a plant with wide range of operating point is collected and passed to a bank of Kalman filters. The Kalman bank contains many parallel filters, called hypothesis filters where each is constructed using a model representing a different operating condition. The output of each filter is compared with that of the hydraulic wind power plant. The filter with the lowest residual represents the most accurate models.

The MMAE generates a weighted average of all Kalman estimated values. The weights are obtained by the $a$ posteriori probability of the residual signals considering a history of input-output variations [28]. These weights can be calculated using

$$P_j(t_i^*) = \frac{f_{z_i|t_i^*,Z_{i-1}}(z_i|h_i, Z_{i-1}) P_j(t_{i-1})}{\sum_{j=1}^{N} f_{z_i|t_i^*,Z_{i-1}}(z_i|h_i, Z_{i-1}) P_j(t_{i-1})},$$

(15)

where

$$f_{z_i|t_i^*,Z_{i-1}}(z_i|h_i, Z_{i-1}) = \frac{1}{(2\pi)^{m/2} |A_k(t_i)|^{1/2}} \exp\left(-\frac{1}{2} r_i(t_i)^T A_k(t_i) r_i(t_i)\right).$$

(16)

In these equations, $f_{z_i|t_i^*,Z_{i-1}}(z_i|h_i, Z_{i-1})$ is the probability density function of the current measurement $Z(t_i)$ conditioned on the hypothesized status and measurement history $Z(t_i)$, based on residual signal $r_k$ and $A_k$. When actual residuals are inconsonance with filter-computed covariance $A_k$, the exponential term in (16) is approximately $[-m/2]$, where $m$ is the measurement dimension.

The output of this block is a vector of probabilities which can be used to weight the state estimates as also shown in Fig. 4. The output of the algorithm is a probability weighted state estimate [28-32].

![Fig. 4. The MMAE filter block diagram](image)

**V. MAIN RESULTS AND SIMULATIONS**

Going through [21] and further research on introduced nonlinear hydraulic wind power system, it can be concluded that the system has 5 states which account for pressure of the pump and motors and speed of the motors. Reading the data from motors speed sensor, they can be sent to the Kalman filters as a measurement for estimating the 3 other noisy pressures in different operating regimes.

Kalman filters and MMAE block diagram has been implemented using MATLAB/Simulink. The estimations of MMAE for the pressures are compared with the exact values from the nonlinear model of system in all possible operating points specified by control and disturbance input (valve position and wind speed respectively) to study the accuracy of...
implemented structure. Considering a 7% maximum error between the exact values from the nonlinear system and MMAE, Fig.5 illustrates 80.75% covering of the operating points by the adaptive estimation. Also Fig. 6 shows that the average of error between nonlinear states and MMAE estimated states is below 4% with a maximum absolute error of 7.8% working on all possible operating points.

Fig. 5. Coverability of the MMAE over the whole operating regime.

Fig. 6. Average of error between nonlinear states & MMAE estimated states

In addition, to clarify the previous results, a comparison between MMAE and the nonlinear model is done by applying an arbitrary profile for wind speed as a disturbance input shown in Fig. 7 to both systems with valve position of 0.35 inch.

Fig. 7. Wind speed profile applied to both systems

Fig. 8 to Fig. 10 depict the performance of state estimation of pressures comparing with the exact values from the nonlinear model.

Fig. 8. Pump pressure estimation, nonlinear system vs MMAE

Fig. 9. Motor A Pressure estimation, Nonlinear system vs MMAE

Fig. 10. Motor B Pressure estimation, Nonlinear system vs MMAE

Fig. 8 to Fig. 10 confirm a close agreement between implemented MMAE and nonlinear system. It can be seen that the state estimation benefits from a good performance even in transients. As the MMAE estimation performance highly dependent on the $Q$ and $R$ noise covariance matrices, their precise estimation reduced their effects of disturbance analysis.
In addition, precise operating point selection was essential in linearization and overall modeling performance improvement. Multiple model adaptive estimation reduced the error in linearized systems. Probability based approach in weighting of linearized model’s state space variables resulted in an excellent operating point inclusion. The overlap areas were reduced to the optimized state that resulted in minimal error.

VI. CONCLUSION

MMAE was applied to adaptively estimate states of a nonlinear hydraulic wind power system in wide operating conditions. This estimation technique uses a bank of Kalman filters, each of which represent a linear model for a specific range of operating point. MATLAB/Simulink was utilized for implementation of the MMAE structure. Accuracy of state estimation using MMAE was also verified by comparison with the nonlinear system. MMAE improved the quality of linear modeling by reducing the state estimation error and including a large range of operating points.

VII. REFERENCES


