Networked Embedded Generalized Predictive Controller for an Active Suspension System

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Abstract—This paper applies the generalized predictive control (GPC) to a class of active suspension automotive systems. It introduces both physical and digital necessary models for simulation and control law design. Experimental environment is designed in order to get real time identification and control verification results. Real time CAN-bus Networked Embedded Control System (NECS) represents the backbone of this environment. Real-Time experimental results show the efficiency of the proposed tuning of the GPC controller in order to get a ride-comfort with an acceptable level of exerted energy.

Index Terms—Active suspension, generalized predictive control (GPC), networked embedded control system (NECS), CAN bus.

I. INTRODUCTION

Control of an active suspension system represents an automotive industrial challenge. Its main objective is to achieve an acceptable behavior, or ride comfort, over a range of working frequencies without exerting too much energy.

An accurate physical modeling for active suspension systems is essential for the design of model-based control techniques [1]. Additionally, a virtual verification environment requires a physical environment model. Car quarter model and actuator dynamics are physically described in [2]. The scope of this paper is limited to these models without detailed addressing of road and human environmental modeling.

Active suspension has a natural nonlinear behavior with respect to road stimulations, in addition to the different high frequency response to the actuator force. It became a benchmark for design and optimization of different types of control algorithms. A linear active suspension model is used with digital sensitivity functions, reshaping control design method [2][3]. Real time implementation of control algorithms over networked systems is addressed in [4].

Generalized Predictive Control (GPC) optimizes an objective function in order to achieve good closed loop response while minimizing the energy over a control horizon [6][7]. Real time software and hardware implementation of model predictive controllers is considered in [8][9][10]. This paper aims at tuning of GPC in real time control environment of active suspension system.

In this work, full physical model of a class of active suspension system is given. An identified digital model is experimentally obtained in order to design and tune a GPC controller. The proposed control algorithm is embedded on a real hardware evaluation board. A communication stack is also integrated in order to handle the digital communication over CAN bus [11]. This paper is organized as follows. In Section 2 a background of the process is given. Section 3 details the complete identification of system models. Section 4 overviews GPC real time implementation issues over NECS. In Section 5 real time experimental extensive tuning results of closed loop GPC is shown. Finally, Section 6 concludes this paper.

II. SYSTEM MODELING

A. Quarter Car Model

The quarter car model has been extensively used in suspension design. It is a simplified model as it can only represent the bounce motion of chassis and wheel without taking into account pitch or roll vibration modes. Figure 1 gives a schematic for quarter car model. The quarter car model is a dynamic system composed of two interconnected subsystems called sprung and unsprung masses. The wheel is connected to the unsprung through a spring/damper pair. A hydraulic actuator force ($F_a$) is used to control the sprung mass vibrations. The existence of a pure damping element parallel with the hydraulic actuator is used to remove shock vibrations.

![Quarter car schematic.](image)

This model can be described by the following system of second-order ordinary differential equations:

\begin{align*}
\ddot{x}_s &= (\frac{1}{m_s}) \left( \ddot{y} - \frac{1}{m_c} x_c \right) - \frac{k_s}{m_s} \dot{x}_s - \frac{c_s}{m_s} x_s + \frac{k_u}{m_s} \dot{x}_u + \frac{c_u}{m_s} x_u - \frac{k_a}{m_s} \dot{x}_a - \frac{c_a}{m_s} x_a + F_a \\
\ddot{x}_u &= (\frac{1}{m_u}) \left( \ddot{y} - \frac{1}{m_c} x_c \right) - \frac{k_u}{m_u} \dot{x}_u - \frac{c_u}{m_u} x_u + \frac{k_s}{m_u} \dot{x}_s + \frac{c_s}{m_u} x_s - \frac{k_a}{m_u} \dot{x}_a - \frac{c_a}{m_u} x_a
\end{align*}
\[ \sum F_{mu} = b_t (\dot{r} - \dot{x}_u) + k_t (r - x_u) + b_s (\dot{x}_s - \dot{x}_u) + k_s (x_s - x_u) - F_u = m_u \ddot{x}_u \]
\[ \sum F_{ms} = b_s (\dot{x}_u - \dot{x}_s) + k_s (x_u - x_s) + F_u = m_s \ddot{x}_s \]

Typical car parameters are derived experimentally in [2] for a high mobility multi-purpose wheeled vehicle.

**B. Actuator Model**

A typical non-linear electro-hydraulic actuator model is developed in [2][2]. It has the following dynamics.

\[
\dot{P}_a = A_P \alpha \left[ C_{d1} w \frac{P_s - sgn(u_1)P_l}{\rho} \sqrt{\frac{2 P_l}{\rho}} - C_{tm} P_l \right]
\]

The essential dynamics of the hydraulic spool have been shown to resemble a first order system [2]:

\[ \tau \dot{u} + u = k v \]

The meaning and numerical values of the actuator parameters identified in [2] are shown in Table 1.

**III. OPEN-LOOP SYSTEM**

**A. Step Response**

Time response of the system is emphasized by applying step inputs, with different strengths, on both the actuator input and the disturbance. Constant road profile is first considered while applying variable actuator voltage inputs over operation range from 1V to 250V. Due to high actuator non-linearity, the time response widely varies as shown in Figure 3.

The steady state is constant regardless the voltage input value. This behavior can be obtained from the mathematical model:

\[ \dot{P}_a = 0, \quad \dot{x}_s = 0, \quad \dot{x}_u = 0, \quad \dot{u} = 0 \]

\[ 0 = A_P \alpha \left[ C_{d1} w \frac{P_s - sgn(u_1)P_l}{\rho} - C_{tm} P_l \right] \]

\[ \left[ C_{tm}/A_P \alpha C_{d1} w \right] \left[ \dot{P}_l - \frac{P_s - sgn(u_1)P_l}{\rho} \right] \]

\[ \left[ C_{tm}/A_P \alpha C_{d1} w \dot{u} \right]^2 \]

Taking into account that \( C_{tm} = 15 \times 10^{-12} \) so the coefficient in the right hand side is approximately zero. So for positive voltage input then:

\[ \dot{P}_l = \frac{P_s - sgn(u_1)P_l}{\rho} = constant \]

The steady state actuator pressure (and so the actuator force) is constant and does not depend on the voltage input. For small actuator input, the actuator response is much
slower than the system. System’s vibration modes appear when relatively high voltage inputs are applied. Now, the response to the road disturbance is shown in Figure 4. The response of the sprung mass is faster than its response due to actuator force.

![Figure 4 Effect of step road profiles](image)

Road profile perturbation highly affects system dynamics. It is also affected by the nonlinear dynamics part. The proposed active suspension model structure is shown in Figure 5. The transfer function \( B(z)/A(z) \) represents the linear transformation between the voltage input and the output. While \( C(z)/A(z) \) represents the internal perturbation of the system due to the high non-linearity of the system. Both \( H_r(z) \) and \( H_v(z) \) are necessary to calculate the GPC digital control algorithm.

![Figure 5: Overall system digital model](image)

A Pseudo Random Binary Sequence (PRBS) is generated from an 11-bit register and a frequency divider equal to four is used [12]. Input magnitude is chosen to be 200V. It is applied to the continuous system model. By using extended recursive least squares method [3][12] on the system output, choosing suitable polynomial order, applying the same PRBS sequence to the obtained model and finally verifying the obtained model using whiteness test, one can obtain the following results:

Order of \( A \) polynomial = 5, Order of \( B \) polynomial = 1
Order of \( C \) polynomial = 6, Process pure delay = 0

\[
A(q^{-1}) = 1 - 3.9704 q^{-1} + 6.4992 q^{-2} - 5.5351 q^{-3} + 2.4597 q^{-4} - 0.4532 q^{-5}
\]
\[
B(q^{-1}) = 0.0002032 q^{-1}
\]
\[
C(q^{-1}) = 1 + 1.1661 q^{-1} + 0.1277 q^{-2} - 0.3083 q^{-3} - 0.0600 q^{-4} - 0.3861 q^{-4} - 0.5024 q^{-5}
\]

The static gain of the transfer function \( B(z)/A(z) \) is 0.1016. This result is expected as the experiment is carried out by applying voltage equals to 200 volt while, as proved, the final output equals to 20 regardless of the applied input. This means that if the experiment is carried out with different voltage input, this will lead to another transfer function with different static gain. The identified model between the actuator input and the system output has two vibration modes at 0.667 Hz and 10.7 Hz.

On the other hand, the digital model of the road effect is driven mathematically from the quarter car continuous model. It is given by:

\[
H_r(q^{-1}) = \frac{0.008862 q^{-1} - 0.0249 q^{-2} + 0.02143 q^{-3} - 0.005318 q^{-4}}{1 - 3.234 q^{-1} + 4.094 q^{-2} - 2.466 q^{-3} + 0.6097 q^{-4}}
\]

The vibration modes of the digital model are at 1.42 Hz and 10.9 Hz. The second sprung mass vibration mode is common in both digital models. Typically, the sampling frequency is 100 Hz.

IV. GPC CONTROL OVER NECS

A. Generalized Predictive Control (GPC)

The generalized predictive control (GPC) belongs to a class of long range model-based predictive control (MPC). GPC was introduced by Clarke and Mothidi [6][7]. GPC output prediction is based upon using CARIMA model:

\[
A(z^{-1})y(t) = B(z^{-1})z^{-d}u(t - 1) + C(z^{-1})\frac{e(t)}{\Delta}
\]

where the un-measurable disturbance is given by a white noise colored by \( C(z^{-1}) \). This polynomial can be used for optimal disturbance rejection, although its role in robustness enhancement is more convincing. GPC uses a quadratic cost function of the form:

\[
f(h_i, h_p, h_c) = \sum_{j = h_i}^{h_p} [C(z^{-1}) [y(t + j) - y^*(t + j)]^2 + \sum_{j = h_i}^{h_p} \lambda [\Delta u(t + j - h_i)^2] ; \lambda > 0
\]

where the initial horizon \( h_i \) is taken equal to or larger than the delay \( d+1 \). The prediction horizon \( h_p \) is taken close to the time response of the system. The control horizon \( h_c \) will define the complexity of the optimization procedure.

The problem of controlling the suspension system can be shown as a regulation problem in which the controller has to reject all disturbances and sustain the vertical movement to zero. Using the canonical RST controller structure, one can describe the control loop as shown in Figure 6, where the set point is fixed to zero and the T-filter used for tracking is omitted [3].
B. Networked and Embedded Control System NECS:
A typical Networked and Embedded Control System (NECS) consists of many Electronic Control Units (ECUs). They represent communicating nodes on a digital network. For active suspension control purpose, each tire has a sensor node and an actuator. Control algorithm exists on a separate node, responsible for acquiring necessary measurements, calculating and sending control signal at each sampling period. Figure 6 shows this simplified NECS system configuration. Controller Area Network (CAN) is typically the physical layer. Network delay is considered into the design of the controller as a process delay [13][14][15].

C. Verification Environment
A Real-Time simulation for the process is carried on Simulink® while the GPC controller calculations are carried on-line on an embedded target. Both PC and target board are connected together using CAN network. This partition is shown in Figure 7 and Table 2.

Table 2: Components used to build verification environment.

<table>
<thead>
<tr>
<th>Process Simulator</th>
<th>Simulink® using Real-Time toolbox</th>
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<tbody>
<tr>
<td>CAN Box</td>
<td>Vector CANcaseXL [16]</td>
</tr>
<tr>
<td>Embedded Target</td>
<td>NEC D70F3441F1 AUTOSAR PHO3 Starter kit which holds a 32-bit NEC automotive oriented microcontroller.</td>
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Volcano Transmission Protocol (VTP®) [17] is used as the communication library on the embedded side. VTP post-build configuration is configured to hold two frames; one for receiving sensor data, and the other for sending data. Each frame holds four signals, which represent one byte of the IEEE float32 representation. A simple encoding/decoding scheme is implemented on both the PC and embedded target in order to encode and decode 32-bit floating-point actuator and sensor data with no loss of accuracy.

V. Real-Time Verification Results
For a non-varying process parameters and/or tuning parameters, GPC will generate the same R-S-T filter. Real-time experiments show only the effect of tuning parameters on the response of the system. In the next section, we will profile the software microcontroller implementation to analyze real-time resources requirements.

A. Testbench Road Track:
Road profile testbench contains four step changes with heights 25, -25, -30 and 30 cm, as shown in Figure 8. This testbench is used in both open and closed loop real time experiments.

B. Performance Evaluation Criteria:

We use Steffens empirical formula which relates the amplitude of vibration causing discomfort as a function of frequency as follow [1]:

\[
X[cm^2] = 7.62 \times 10^{-3} \left(1 + \frac{125}{f^2}\right)
\]

C. Open Loop Response of the Test Bench:
The open loop response for the system on the test track is represented in Figures 9-10. Analyzing sprung mass vibration analyzed by FFT along with the comfort assessment shows the existence of energetic frequency components at low frequencies which lead to sick human feel.

D. Tuning GPC parameters:

Several experimental tests are done to achieve an acceptable closed-loop performance. Colored noise filter of GPC is chosen equal to 1, the same for the scaling coefficient $\lambda$. Initial horizon should be chosen to be larger than system delay. Since the system suffers only from unit network delay, then it is adequate to choose the initial horizon equals to 2. The major challenge will appear while choosing prediction horizon.

In this section we will show the closed loop response due to different choices of prediction and control horizons. The main objective is to reject external road profile disturbances. We will treat the external road disturbance as un-measurable modeled disturbance. Then, it is adequate to insert the pulse transfer function of $H_r(z)$ as a fixed part in the S-Filter while calculating the control law [3]. This is expressed by,

$$S(q^{-1}) = Hs(q^{-1}) \tilde{S}(q^{-1})$$

where $Hs(q^{-1}) = \text{denominator of } H_r(z)$

The previous procedure can also be interpreted as shaping the output sensitivity function ($S_y$) by adding a pair of undamped poles located at the disturbance frequency. Using this scheme, by adding two undamped roots at frequency = 10.9 Hz, one gets the following filter parameters:

$$Hs(q^{-1}) = 1 - 1.0083 \, q^{-1} + 0.2542 \, q^{-2}$$

To emphasize on the effect of the sensitivity function shaping, we start by choosing arbitrary tuning parameters. Figures 11-12 show the results of using GPC controller with prediction horizon set to 80 and control horizon set to 10 without the pre-specified filter. The closed loop response is shown to be worse than the open-loop response.

Applying the sensitivity function shaping procedure for the same tuning parameters leads to better results at the low frequency range of the amplitude spectrum which is decreased dramatically while increased in the mid frequency range as shown in figures 13-14.

Different prediction and control horizon lead to a tradeoff between having energetic components in either the low frequency or the mid frequency range. Increasing prediction horizon to be near the time response of the actuator and increasing the control horizon leads to acceptable results. It has relatively good settling time, human sick feel in both low and mid frequency range and better power consumption as viewed by the control signal. These results are shown in Figures 15-17.
A digital model for an active suspension system is used in order to tune GPC controller. Perturbation model is implicitly considered while designing the control algorithm. This challenging process needs special tuning parameters that complicate GPC software implementation in real time. This work presents a compressive verification environment over a real CAN bus NECS. This includes legacy simulation, e.g. Matlab, CAN frames acquisition, and communication stack on PC and on hardware control board.

GPC control appears to give an acceptable closed loop performance while maintaining the optimal power in the active suspension system. The main problem facing a real-time implementation is the obligation of using large prediction and control horizons due to fast sampling rate which is chosen based on the fast time response of the external disturbance compared with the process time response. Future work is needed to implement Real-Time hardware for online GPC controller for such cases.

VI. CONCLUSION

REFERENCES

[16] www.vector.com