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Effect of Smaller Output Horizon in Neural Generalized Predictive Control

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Abstract—**This paper deals with the effect of small prediction horizon in Neural Generalized Predictive control. A different strategy is proposed to overcome the problem of estimation at each sampling instant. In this method the parameter are estimated at a large sampling interval and control increments are calculated at a smaller sampling interval. Simulation studies are presented to show the merits of smaller prediction horizon over larger prediction horizon. Studies are presented to show the merits of smaller prediction horizon over larger prediction horizon and enable one to use variable output horizons, resulting in considerable saving of cost of simulation and computer time.**

Index Terms— **longer Predictive control, larger sampling interval, neural network. Neural Generalized predictive control (NGPC), prediction horizon (LPH), Smaller Prediction horizon (SPH), smaller sampling interval**,

1. INTRODUCTION

Generalized predictive control (GPC) belongs to the class of digital control methods called Model-Based Predictive control (MBPC) and was introduced by Clarke and his co-workers in 1987 [1,2].GPC is known to control non-minimum phase plants, open loop unstable plant and plants with variable or unknown dead time and originally developed with Linear plant predictor model. The ability of GPC to make accurate predictions can be enhanced in a neural network is used to learn the dynamics of the plant [3, 4]. This application combines the advantages of predictive control and neural network, known as Neural generalized predictive control (NGPC) developed by Donald Soloway, 1996 [5]. The NGPC algorithm operates in two modes, i.e. prediction and control. It generates a sequence of (future) control signals within each sampling interval to optimize the control effort of the controlled systems. In NGPC the control vector calculations are made at each sampling instant. These computations may be complex depending on the tuning parameters. They are (I) control horizon (ii) Prediction (or) Output horizon.

IINEURAL GENERALIZED PREDICTIVE CONTROL

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The NGPC consists of four components, the plant to be controlled a reference model that specifies the desired performance of the plant, a neural network models the plant and the cost function minimization (CFM) algorithm that calculates the input needed to produce the plant's desired performance. The NGPC algorithm consists of the CFM block and the neural net block.

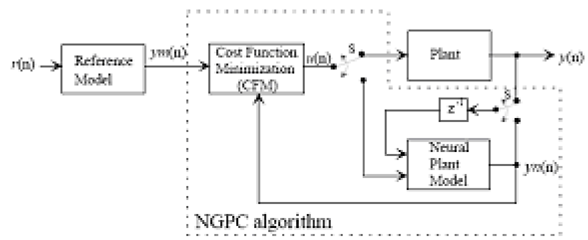

Figure 1 Block Diagram of NGPC system and Algorithm

The NGPC algorithm has the following important steps [6]

1) Generate a reference trajectory. If the future trajectory of Ym (n) is constant for the future trajectory,
2) Start with the previous calculated control input vector, and predict the performance of the plant using the model,
3) Calculate a new control input that minimize the cost function,
4) Repeat steps 2 and 3 until desired minimization is achieved,
5) Send the first control input, to the plant,
6) Repeat entire process for each time step.

NGPC is based on minimizing a cost function over a finite prediction horizon. The cost function of interest to this application is [6];

$$J = \sum_{j=N_1}^{N_2} \left[ym(n+j) - yn(n+j) \right]^2 + \sum_{j=1}^{N_u} \lambda_u(j) \left[\Delta u(n+j) \right]^2 + \sum_{j=1}^{N_u} \left(\frac{s}{u(n+j) - u_{\min} + \varepsilon} + \frac{s}{u_{\max} - u(n+j) + \varepsilon} \right)$$

where
N1 is the minimum-costing horizon,
N2 is the maximum-costing horizon,
Nu is the control horizon,

ym is the desired tracking trajectory,
Yn is the predicted output of the model

λ_u is the control input weighting factor,

$$\Delta u(n+j) = u(n+j) - u(n+j-1)$$

The s and ε parameters are used to prevent for locking of the ANN and selected very small.

III. DIFFERENT STRATEGY

In NGPC the control vector calculations are made at each sampling instant. The estimation at each sampling instant is costly and hence is not desirable and even poses problems if the sampling period is too small. In general the following difficulties may arise due to smaller sampling period.

(i) On-line parameter estimation and its computation is quite complex and even may take considerable time

(ii) The numerical errors may become prohibitively large

(iii) The reduced order model may not be robust with regard to a smaller sampling period. A different strategy is proposed to overcome the above problems.

A. For SPH the control increments are calculated using the following algorithm.

(1) The free response is computed based on the estimated model and known data and is compared with set point sequence.

(2) Using the user chosen values for initial and final values of horizon, the incremental control vector is calculated over the smaller prediction horizon by minimizing the performance index J to determine best input U.

(3) The first element of the incremental control Vector U is calculated and this control element only is applied to the plant model.

(4) The first element of the input sequence is asserted and the appropriate data vector is shifted so that calculations can be starting from evaluated parameters of the given model.

(5) The procedure can be continued till the end of larger prediction or if it can be stopped by using a termination criterion, when it reaches the set point.

IV SIMULATION STUDIES

Extensive simulation studies have been carried out to show the importance of smaller prediction horizon (SPH) and compared with larger prediction horizon (LPH) with regard to time taken to reach the set point (W) The simulation studies are explained below:

A. Constant Set Point: LPH was chosen as 20. SPH was considered for two different values for the purpose of comparison with LPH. It was chosen as 5 and 3 respectively. Simulations were also carried out with a delay of one sampling period.

B. Variable set Point: The second order plant was simulated for a variable set point.

C. Variable Output Horizon: The advantage of smaller prediction horizon can very well be utilized to fix the prediction horizon based on some criterion which leads to what is called variable output horizon. To illustrate this simulation studies were conducted on the same second order plant, both without delay and with delay on the same second order plant for SPH values of 3 and 5.

Simulation studies were also conducted on a third order plant model using the same procedures with and without variable set point.

So the small prediction horizon enables one to use a variable output horizon with which one can achieve considerable reduction in the number of predictions. This reduces estimation cost as well as time.

V COMMENTS

Fig 2 shows the time required to reach the set value 5.0 for both LPH and SPH is about 10 sampling period for a second order system. Therefore, SPH can be preferred as it reduces the effort required for estimation problem.

Fig 3 shows that with SPH (3 and 5) the steady state error is reduced to Zero at the 10^{th} and 14^{th} sampling periods respectively. It is also observed that though there is a step variation from 5-10, and 10-5 the response due to SPH was unaltered. Also the robustness was maintained.

Fig 4 The time taken to reach the set point is 18 sampling periods for 5-10 change and 36 sampling periods for 10-5 change and in all for a set value of 5, 10,5,10 the over all time required is about 72 sampling periods as against 200 sampling periods when the fixed horizon is used. So the smaller prediction horizon enables one to use a variable output horizon with which one can achieve considerable reduction in the number of predictions. This reduces estimation cost as well as time.

Fig. 5 shows the response of the plant after the change in dynamics. Its behavior was unaltered. Simulations were also conducted with variable set point Fig.6 and 7 depict the same trend as in Fig. 3 and Fig. 4.

Fig .6 shows the time required to reach the set value 5.0 for both LPH and SPH value of 5 is about 11 sampling periods. For SPH values 3, it is about 14 sampling periods. When simulated with a delay of one sampling period both LPH and SPH value of 3, it is about 14 sampling periods. When simulated with a delay of one sampling period both LPH and SPH value of 5 reach the set value in about 14 sampling periods. For SPH value of 3 it is about 18 sampling periods. Fig 8 shows the same trend for third order plant

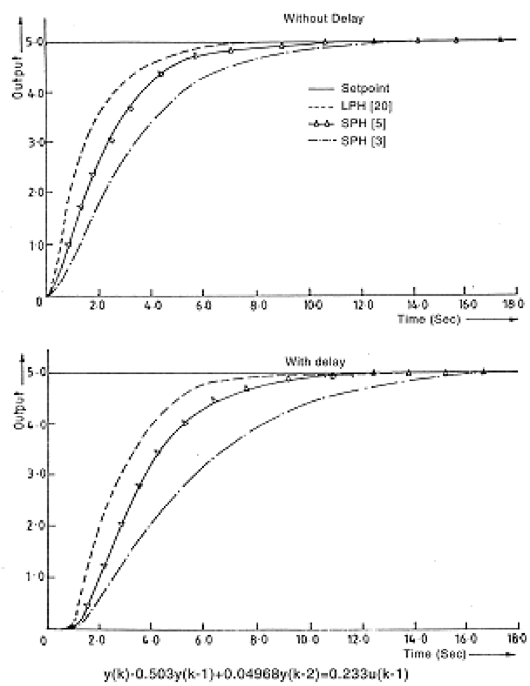

Fig.2

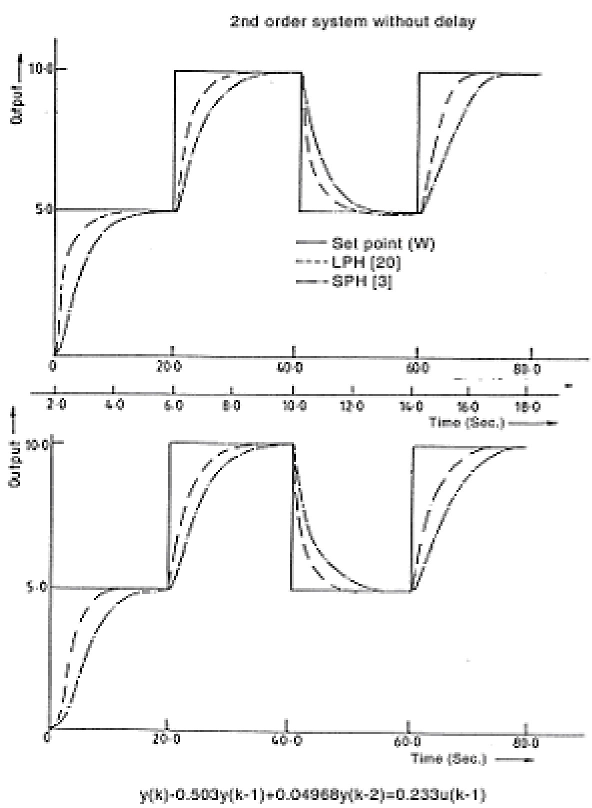

Fig. 3

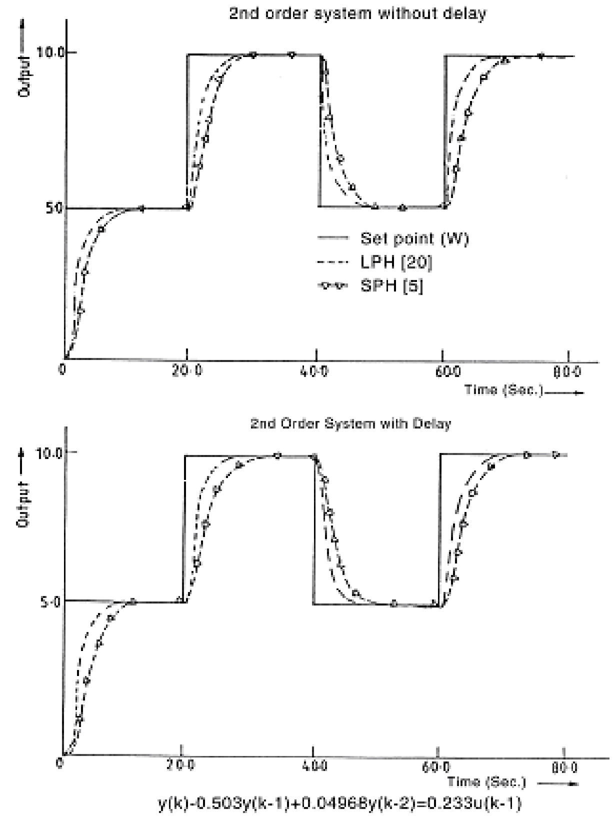

Fig. 4

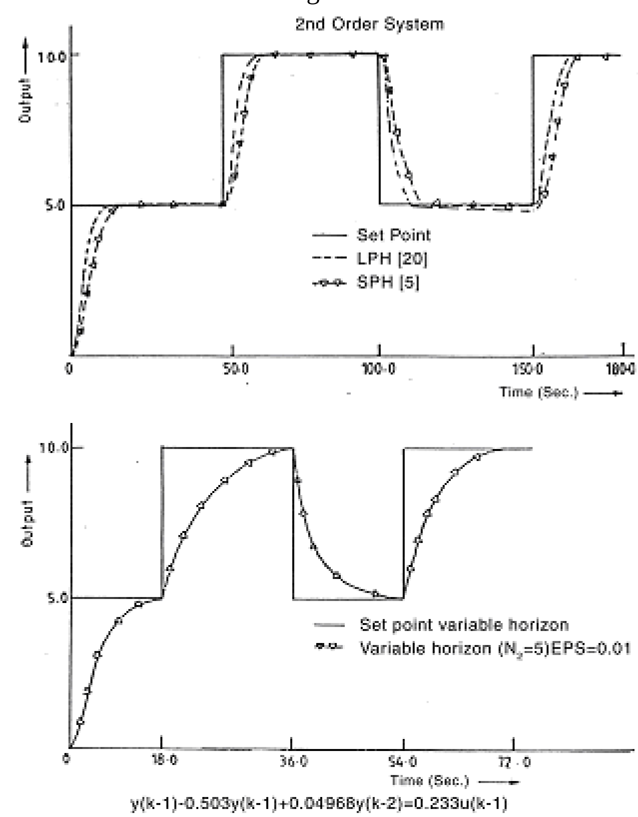

Fig. 5

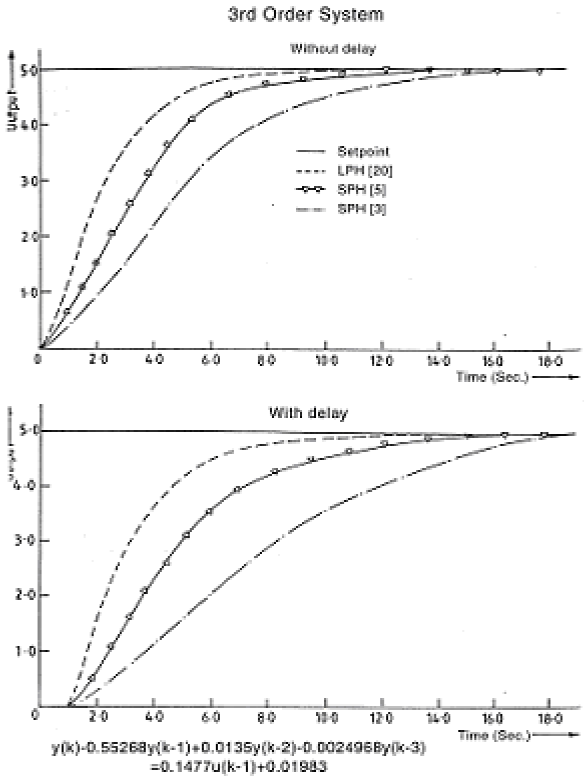

Fig. 6

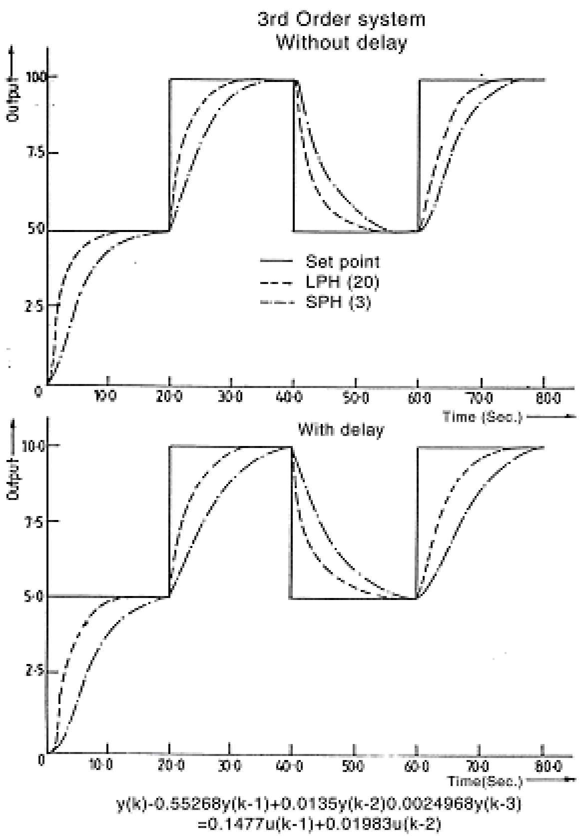

Fig. 7

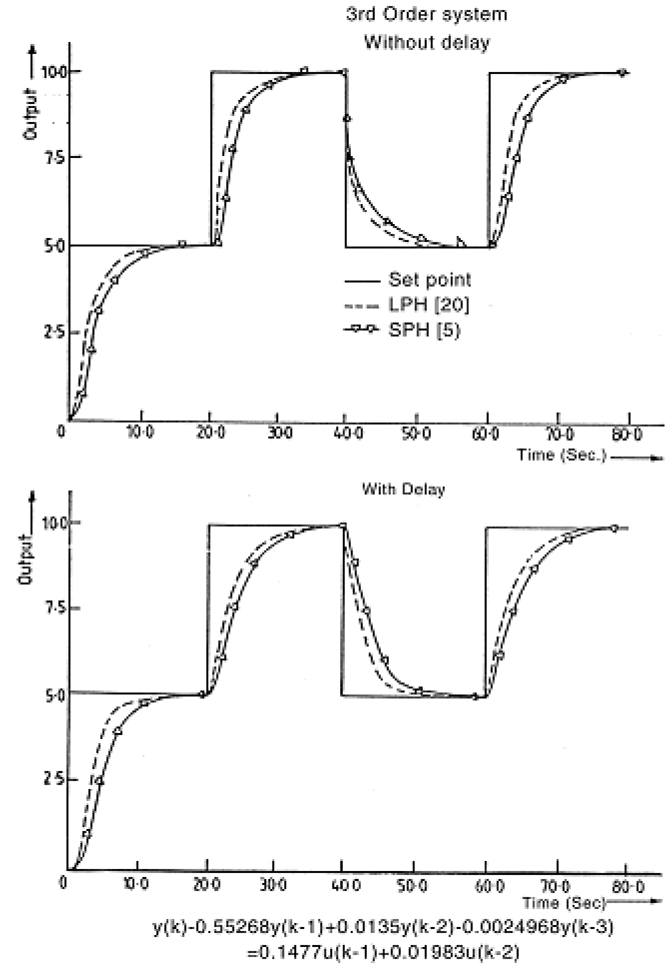

Fig. 8

VI CONCLUSIONS

Different strategy is proposed for implementation of NGPC algorithm. The application of constant control action over the known horizon stabilizes the system near the set point faster with improved response. Smaller prediction horizons enable one to use variable output horizons, resulting in considerable saving of cost of simulation and computer time. This reduces the no. of predictions by about 60%. But smaller prediction horizon has a drawback of slow rise of the transient response.

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