A review of model predictive control and closed loop system identification for design of an autopilot for uninhabited surface vehicles

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Abstract

Uninhabited surface vehicles (USVs) are playing an increasingly significant role in modern marine operations in shallow waters and in the oceans. The plethora of opportunities and threats that come with modern day living have created a niche demand for USVs to perform missions faster, more autonomously and with a great-deal of flexibility. In order to meet these demands, a control system for an USV needs to be designed appropriately to enable it to cope with these real-life requirements. Chemical and process industries have successfully used model predictive controllers and closed loop system identification to improve efficiency of the overall system performance. This report aims to provide an introduction into some of these topics that have been developed and explore the suitability of adapting these techniques to design and develop an adaptive autopilot for an USV.

Keywords: *autopilot design, uninhabited surface vehicles, model predictive control, closed loop system identification*

1. INTRODUCTION

Human beings have fantasised about being able to control objects and to perform missions remotely from time immemorial. With the limited knowledge at that time, witchcraft and religion attempted to achieve the same. It was not until 1898 that this fantasy was transformed into reality by an engineer, Nikola Tesla. He coined the word 'tele-automation'. Despite being ahead of his time, Tesla was unsuccessful to sell his patent to the US Defense department and further developments along these lines were stalled. This is an example of how the technical advances are shaped by key business decision makers. Few other engineers made unsuccessful attempts to interest the business community with their patents for such similar vehicles. However, recently, there has been turn of tide and there has been increased interest both in academia and in industry to develop such vehicles. As technology progressed, remotely operated vehicles evolved to be capable of performing autonomous missions and are also known as autonomous surface vehicles (ASV) and unmanned surface vehicles (USV). However, the term 'unmanned' is being replaced by 'uninhabited' in recent literature (Roberts and Sutton, 2012).

USVs are finding a niche in costal and estuarine systems as a tool for rapid and cost effective deployment platforms for environmental monitoring and assessment. One such example is an USV developed by University of South Florida. It has been developed specifically for environmental monitoring (Steimle and Hall, 2006). Similarly the *Springer* is a unique academic research platform in UK developed by Plymouth University and is designed for environmental monitoring (Bertram, 2008). Furthermore, a detailed survey of the different USVs used by different military and other research organisations is described in detail by Bertram (2008) and (Motwani, 2012). Also, Olin College of Engineering have developed an USV which is very similar to *Springer*. It also serves as a low cost educational platform for scientific research. Further details about this USV can be found in Holler, et al., (2008). Another catamaran style ASV which is similar to *Springer* is presented by Wang, et al., (2011).

Currently, USVs are successfully deployed for military operations, search and rescue missions and environmental monitoring, to name a few applications (Motwani, 2012). *Springer* is also capable of undertaking such missions. Despite the advances in modern electronics, communications and engineering in general, the technologies and the theoretical concepts used in current USVs are still in their infancy. It necessitates enduring the development of the existing technologies used in USVs. Before attempting to progress along these lines, one has to be aware of the current and recent developments in this field to identify the gaps in the current literature and to progress the research further to answer the worthwhile research questions.

The report is organised as follows, section 2 describes the system overview and explores the recent developments of USV guidance strategies. Current trends in marine control systems are presented in section 3. Rigid body modelling approach is presented in presented in section 4. Different system identification techniques are presented in section 5 while section 6 introduces model predictive control. Closed loop system identification and closed loop performance assessment are discussed in sections 7 and 8 respectively. Finally, concluding remarks are given in section 9.

2. SYSTEM OVERVIEW

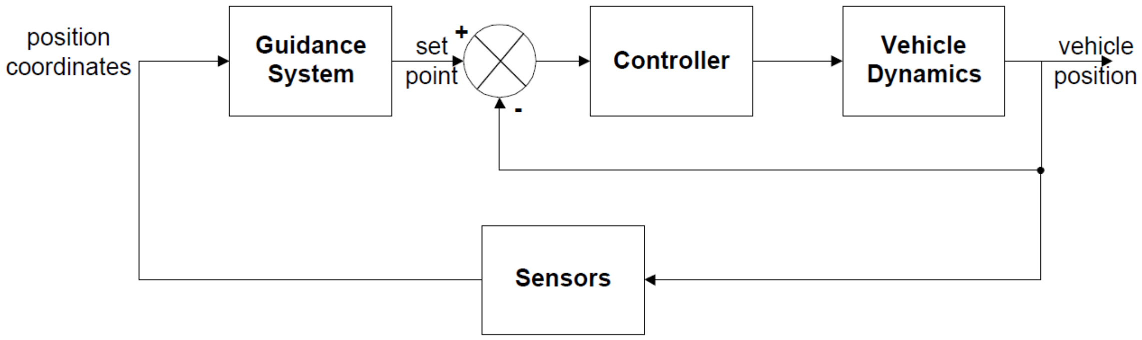

Figure 1: Guidance and control for a vehicle

The Navigation, guidance, and control (NGC) systems are the fundamental blocks that enable vehicles to operate autonomously. The system overview and the relation between the different subsystems of USV are illustrated in figure 1. The navigation subsystem is concerned with determining the current location of the vessel and is achieved by collecting online, real time data from its sensors. The guidance system decides the best possible physical trajectory to be followed by the vehicle. Guiding an automatic vehicle along a desired trajectory has been further explained by Freund and Mayr (1997). The guidance system gets its input from the navigation system and generates the required reference headings. The control system is responsible for keeping the vehicle on course as specified by the guidance processor.

2.1 Guidance strategies

A survey of different guidance strategies is discussed in detail by Naeem, et al.,(2003). Two of the main strategies will be discussed here:

(i) Line of sight
(ii) Proportional navigation

2.1.1 Line of sight guidance

Line of sight (LOS) guidance is the commonly used simple guidance strategy. The line of sight angle λ between the target and the vehicle can be easily obtained by the following equation (1)

$$\lambda = \tan^{-1}\left[\frac{y_2 - y_1}{x_2 - x_1}\right] \qquad (1)$$

where (x_1,y_1) is the current location of the *Springer* and (x_2,y_2) is the target position required for the *Springer*.

2.1.2 Proportional navigation guidance

Proportional navigation guidance (PNG) was initially used in the guidance of missile systems and it can be mathematically represented as show in the following equation (2).

$$\eta_c = N' \, V_c \, \lambda \tag{2}$$

where η_c is the acceleration command, N' is the navigation ratio, V_c is the closing velocity and λ is the LOS angle rate. The advantage of this law is that the variation of N' results in better performance. More variations of PNG law and a comprehensive view of other different guidance systems can be found at Naeem, et al., (2003)

2.2 Waypoint guidance by LOS

The most common guidance scheme used in autonomous vehicles is waypoint guidance by LOS (Naeem, et al., 2003). In this scheme the guidance between two points $[x_d(t_o), y_d(t_o)]$ and $[x_d(t_f), y_d(t_f)]$ is achieved by splitting the path between them into a number of way points $[x_d(k), y_d(k)]$ for $k = 1, 2, \ldots, N$ as shown in the following figure 2.

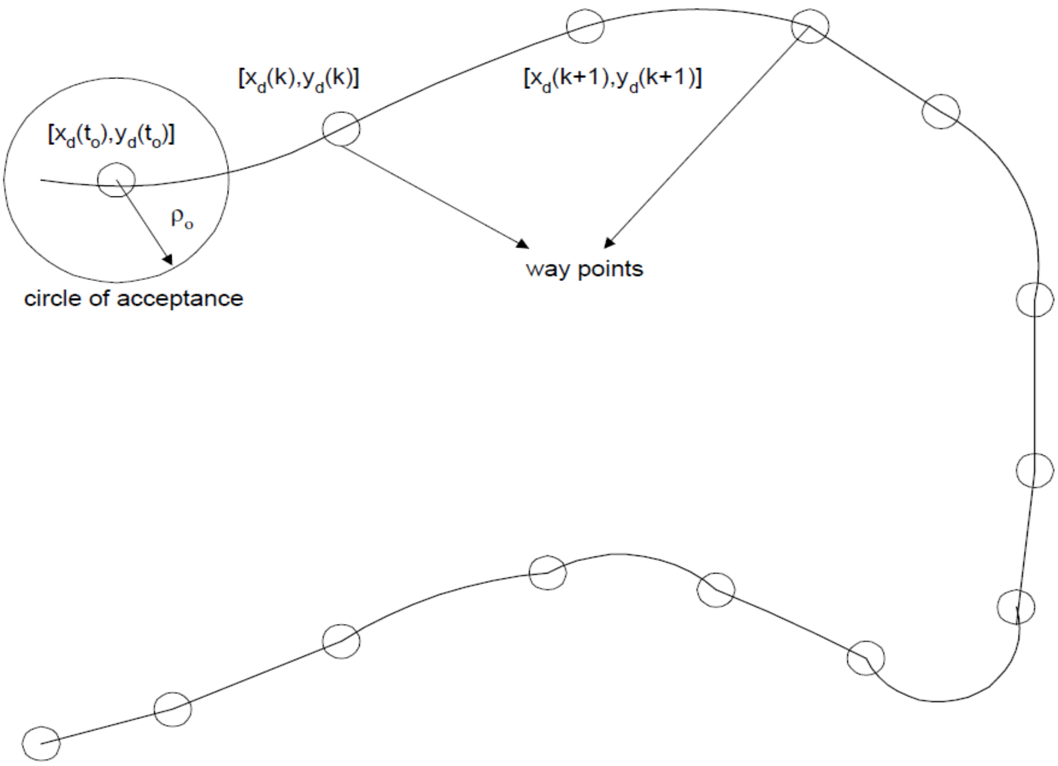

Figure 2: Way point guidance by LOS

The LOS of the desired heading angle is given by the following formula (3)

$$\lambda = \tan^{-1}\left[\frac{y_d(k) - y(t)}{x_d(k) - x(t)}\right] \tag{3}$$

where [x(t), y(t)] is the current location of the vehicle. Moreover, Healey and Lienard (1993) suggest that the circle of acceptance should be at least twice the length of the vehicle. For *Springer* the length is approximately 4m, thus the circle of acceptance is 8m. The error between the vehicles current location and the waypoint [x_d (k), y_d (k)] is computed and checked if it satisfies the following condition (4)

$$\rho^2 = [x_d(k) - x(t)]^2 + [y_d(k) - y(t)]^2 \leq \rho_0 \quad (4)$$

where ρ_0 is the radius of the circle of acceptance.

A decentralised controller based on a receding horizon control (RHC) scheme was designed by Borrelli, et al., (2004) to avoid collision. Predictive control and guidance strategy for a nonlinear unmanned aerial vehicle has been presented by Anderson and Stone (2007).

A way-point guidance scheme based on a LOS algorithm has been presented by Moreira, et al., (2007). Research and design aspects of *Springer*'s navigation, guidance and control (NGC) systems and their implementation in the USV are presented by Naeem, et al., (2008) Experimental results for multiple waypoints following algorithm is also discussed in this paper. Oh and Sun (2010) present an MPC scheme with LOS path generation capability for a way-point tracking of under actuated surface vessels. The inclusion of LOS decision variable into the MPC design results in path performance improvement. Biologically inspired strategies for the guidance of autonomous vessels are presented by Srinivasan (2011). Whilst a model reference adaptive control algorithm in parallel with an analytic MPC is presented for path following of under actuated ships along a predefined path at a constant forward speed by Xiaofei, et al., (2011).

3.1 Trends in marine control systems

Roberts (2008) presents a clear picture of the trends in marine control. The only limitation of this study is that the author has considered only the events sponsored by International Federation of Automatic Control. Nevertheless, the study engenders assurance regarding the trends in marine control by considering 750 papers and 13 conferences over a period from 1992 to 2008.

Sperry and Minorski developed the first steering autopilots (Roberts, 2008), (Sharma, et al., 2012). Their pioneering work led to the introduction of PID (proportional-integral-derivative) controllers for automatic ship steering. Fossen (2000) reasons that the PID controller was a result of an important advance in ship control systems design which was fostered by invention of electrically driven gyrocompass.

First full scale trails using LQG and H-Infinity controllers for the integrated fin rudder roll stabilization was reported by Roberts, et al., (1997). Parallel multi-model control system or switch control systems is obtained by designing a bank of controllers for different ship speeds, sea states and encounter angles to automatically switch to appropriate controller (Narendra and Balakrishan, 1997) whereas Ippolitti, et al., (2006) report the work of switched control for unmanned underwater vehicles (UUVs).

Researchers have made considerable progress in applying intelligent systems such as fuzzy logic, artificial neural network (ANN) and a combination of these systems into marine systems. Polkinghorne, et al., (1995) report the first commercial fuzzy autopilot. Craven (1999) reports the use of adaptive network based fuzzy inference system (ANFIS) to develop control strategies for UUVs. Though the intelligent systems performed well in simulation studies, application in real life systems produced performance and stability issues. Hence, these techniques are still not widely used in practical applications. Conversely, PID controllers have remained the industry standard for automatic control systems despite many advances in the control systems theory, mainly due to their reliability and simplicity.

Another area of interest in marine control systems is the control of rudder systems. Stafford and Osborne (2008) advocate the use for electrical actuation of hydrodynamic control surfaces for rudder systems as it allows faster rudder speed and has significant advantages over hydraulically operated counterparts.

Passenger comfort and stability of cargo were the driving factors which necessitated the development of control systems designed to achieve roll stabilisation. In case of USVs there is no need to investigate this any further as it is devoid of passengers and heavy cargo. Hence, it is sufficient to limit the discussion of USV autopilots to heading or yaw control. Whilst, most of the advances presented in this section are concerned with ships and some UUVs. Developments related to USVs will be discussed in the next section.

3.2 Development of USVs

Fifteen years of development of USVs are presented by Manley (2008) and more recent developments of USVs are presented by Motwani (2012). Some of the early technologies which enabled the development of USVs and the future outlook of USV technology are described in these papers. During the trials of the first USV (named ARTEMIS) built at Massachusetts institute of technology in 1993, it was observed that the small size was a big limitation and it seriously undermined the mission capabilities by reducing the sea-keeping and endurance. Modification and design iterations of the USV resulted in better efficiency and it was able to perform missions in the real world. Around 2003, the US Navy revealed its “master plan” with its focus on development and deployment of USVs. Yet again, it was a demonstration of how the business users drive the technical advances. It merely took 105 years for the US Navy to be interested in Tesla’s tele-automation!

On the other hand, USVs have been successfully utilised in survey missions since 2000 and different experiments have been conducted by different teams around the globe using various hull shapes (Alves, et al, 2006). Most of the academic institutions have opted for catamaran type USVs due to operational flexibility and practicality (Ferreira, et al., 2006). *Springer* is an USV developed by Plymouth University around the same timeline and was slightly ahead of the ROAZ (catamaran built by a Portuguese research team at Instituto Superior de Engenharia do Porto) and the sea surface autonomous modular unit (SESAMO) utilised *Charlie* USV (built by an Italian research team at Instituto Superior de Engenharia do Porto). It is noteworthy to mention that SESAMO was used in harsh environmental conditions of Antarctica to support ocean research (Caccia, et al., 2005).

Another interesting hybrid is the semi-submersible platform developed in partnership with ASV Ltd. The hull of the vehicle remains submerged underwater and the mast for communication and air exchange remains outside the water level (Phillips, et al., 2008). Being submerged underwater enables the vehicle to utilize better propulsion systems and exhibits greater passive stability. However, the electronics have to be encased in a sealed water tight compartment and it is not as flexible and practical like a catamaran hull.

The twin hull design of *Springer* has certain advantages such as positive buoyance; it is practically unsinkable even if there is a hull penetration. Thus it provides the valuable time required to perform rescue or repair. The other advantage is that the presence of twin motors.

3.3 Modelling a hybrid power system for an USV

Other areas of development of electrically powered USVs are to increase the battery life so that the USV could perform missions which require longer operational periods. Long endurance of USVs can be achieved by using solar panels and wave power by Hine and McGillivary (2007). Nevertheless, the speed of such a vehicle is very low and makes it suitable only for passive surveillance missions.

A hybrid power system has been designed by combining the solar array, an ocean wave energy converter, a fuel cell system, a diesel generator and a lithium ion battery pack by Khare and Singh (2012). Incorporating all these changes into *Springer* to improve endurance will become another research project in its own right. To achieve a balance between the modernisation of *Springer* and the time spent, it is practical to charge the rechargeable batteries on board via the solar panels to increase the mission durations. Hence solar panels will be installed in *Springer.*

Having discussed the trends in marine control and the developments of USV's, the next section will present the approaches available for modelling the vehicle dynamics.

4. Rigid body modelling approach

Fossen (2011) suggest that the generalized six degree of freedom rigid body equations of motion for the vehicle can be taken as follows :

$$\mathbf{M}_{RB}\dot{v} + \mathbf{C}_{RB}(v)v = \tau_{RB} \tag{5}$$

Here $v = [u\ v\ w\ p\ q\ r]^T$ represents the linear and rotational motions of the rigid body in a body-fixed coordinate system. $\mathbf{M}_{RB}$ is the rigid body inertia matrix satisfying

$$\mathbf{M}_{RB} = \mathbf{M^T}_{RB} > 0, \quad \dot{\mathbf{M}}_{RB} = 0 \tag{6}$$

and the $\mathbf{C}_{RB}$ corresponds to the Coriolis and centripetal forces that can be parameterized to a skew symmetric matrix, ie,

$$\mathbf{C}_{RB}(v) = -\mathbf{C^T}_{RB}(v) \tag{7}$$

$\tau_{RB} = [X\ Y\ Z\ K\ M\ N]^T$ is a generalized vector of external forces and moments about the origin acting as an input to the system. For many USVs, the depth z and pitch θ variables are not applicable. Also the roll ϕ variations were found to be negligible and thus ignored. Therefore expanding equation (7) with reference to the above statements results in the following four equations:

$$m[\dot{u} - vr - x_G(r^2) - y_G\dot{r}] = X$$

$$m[\dot{v} + ur - y_G(r^2 + p^2)] = Y$$

$$\mathrm{rpl_x} - \dot{\mathrm{p}}\mathrm{l_{xy}} - \mathrm{mx_G(vp)} = \mathrm{N} \tag{8}$$

It can be noted that by coinciding the centre of gravity with the origin, the above equations can be simplified further. Nevertheless, the intention as always is to model the yaw dynamics of the vehicle and thereby gain an insight to the behavioural characteristics of the system.

Unfortunately hydrodynamic modelling is usually very expensive, time consuming and requires the use of specialist equipment in the form of a tank testing facility. However, the approach does produce detailed models based upon hydrodynamic derivatives. In addition, costs can also rise further if vehicle configurations change and thus, the tank testing and modelling procedure have to be repeated. Since the hiring and running costs for such a facility were deemed to be prohibitive, it was considered more appropriate to model the vehicle dynamics using Black box identification techniques.

5. System identification

System identification (SI) methods compose a mathematical model, or series of models, from measurements of inputs and outputs of dynamic systems. The extracted models allow the characterisation of the response of the overall system or component subsystem (Tischler, 1995). To build an efficient controller it is essential to capture the dynamics of the operating vehicle as accurately as feasible. Obtaining the parameter-estimation of the marine vehicles is nonlinear and multivariable (Fossen et al, 1996). Hence a nonlinear model of USV needs to be used in the controller design to reflect the dynamics of the vehicle accurately.

Basically, the SI approach is a Black box modelling technique used extensively in the general control systems engineering community (Ljung, 1999). Ljung (2010) offers a comprehensive perspective on SI and he argues that thought SI is a very large topic, with different techniques that depend on the character of the models to be estimated: linear, nonlinear, hybrid, nonparametric, etc., a small number of leading principles is sufficient to characterise the entire area. Ljung (2010) recommends that one's main focus should be concerned with obtaining a sustainable description by proper decision in the triangle of model complexity, information contents in the data and effective validation.

Moreover, SI has also been detailed in Sutton, et al.,(2011), only a brief note on this approach is given here. It consists of the subsequent steps:

- Data collection: During this first phase the input/output data of the system to be identified is gathered.
- Characterization: Here the aim is to define the structure of the system to be identified and the selection of suitable model architecture.
- Identification/estimation: This involves determining the numerical values of structure parameters that minimize the error between the system to be identified and its model.
- Validation: Model validation consists of relating the system to the identified model in the time or frequency domain to instil confidence in the model obtained.

Various other methods currently used to obtain a nonlinear model of an USV are discussed as follows:

5.1 Neuro-fuzzy local linearization process models

Fuzzy local linearization (FLL) is a useful divide and conquer method for coping with complex problems such as data-based nonlinear process modelling (Harris and Gan, 2001). Neuro-fuzzy state estimation has been used in this work.

5.2 Neuro-fuzzy methods for nonlinear system identification

Babuška and Verbruggen (2003) also reiterate the fact that nonlinear SI improves controller performance and achieves a robust fault-tolerant behaviour. Among the different nonlinear identification techniques, methods based on neuro-fuzzy models are gradually becoming established not only in the academia but also in industrial applications. Neuro-fuzzy modelling can be regarded as a grey-box technique on the boundary between neural networks and qualitative fuzzy models. The tools for building neuro-fuzzy models are based on combinations of algorithms from the fields of neural networks, pattern recognition and regression analysis.

5.3 Wavelet analysis for system identification

Wavelet transfer is relatively a new tool and its key strength is its ability to reduce noise and data. The two most commonly used forms of wavelet transforms are continuous wavelet transform (CWT) and discrete wavelet transform (DWT) (Leavey, et al., 2003). A wavelet based SI method has been utilised by Ashino (2004) to perform SI of an USV. Kiran, et al.,(2009) have utilised DWT for SI. Here the excitation signal has been chosen such that it gives an orthogonal inner product in the DWT at some step size (the authors have chosen step size 2). Unfortunately, the system impulse response can only be estimated at half the available number of points of the sampled output sequence. This problem is overcome by over sampling the system output. From the simulation results, the authors found that this method of system identification of a variety of finite and infinite impulse response systems is far better than other conventional system identification methods.

5.4 Observer Kalman filter identification

The Observer Kalman filter identification (OKID) method has been applied by Tiano et al (2007) to obtain the linear discrete-time multivariable models of an UUV. Elkaim (2009) performed several system identification passes to excite system modes and model the dynamic response of an USV. The identification process used the OKID method for identifying a linear time invariant plant model and associated pseudo-Kalman filter. System identification input was generated using a human pilot driving the catamaran on roughly straight line passes. A fourth order discrete time model was generated from the data, and showed excellent prediction results.

Various system modelling techniques were presented in this section. Current literature suggests that SI is a practical, economic, flexible and less time consuming way to obtain a model of the operating vehicle.

6. MODEL PREDICTIVE CONTROL

MPC refers to a class of algorithms that compute a sequence of manipulated variable adjustments in order to optimize the future behaviour of a plant. Originally developed to meet the specialized control needs of power plants and petroleum refineries, MPC technology can now be found in a wide variety of application areas including chemicals, food processing, automotive, aerospace and metallurgy. The development of MPC can be traced back to 1978 after the publication of the paper by Richalet et al.,(1978). They named their algorithm model predictive heuristic control (MPHC) and it was successfully applied to a fluid catalytic cracking unit main fractionator column, a power plant steam generator and a poly-vinyl chloride plant. Then, Cutler and Ramaker(1980) who worked in the Shell Oil Company between 1979 and 1980 developed their own independent MPC technology referred to as dynamic matrix control (DMC), and they showed results from a furnace temperature control application to demonstrate improved control quality. However, another form of MPC, called generalized predictive control (GPC) was devised by Clarke et al.,(1987). The fundamental difference between all these techniques is the type of model used and the cost function being optimized. Moreover, the evolution of major MPC algorithms is illustrated by the following figure 3.

The first generation of MPC technology was dominated by dynamic matric control (DMC) algorithm and identification and command (IDCOM) software. Second generation MPC technologies like quadratic dynamic matric control (QDMC) were able to handle the input and output constraints in a systematic manner (Jounela, 2007). The third generation MPC algorithms such as Hierarchical constraint control (HIECON), Predictive functional control (PFC), Shell multivariable optimizing control (SMOC) were able to distinguish between the different level of constraints (hard, soft and ranked). Competition and mergers in the industry resulted in two major fourth generation MPC algorithms; robust model predictive technology (RMPCT) is offered by Honeywell and DMC-plus is offered by Aspen technologies. The fourth generation MPC algorithms are capable of prioritizing different control objectives, handling model uncertainties (by using prediction error methods and sub-space methods). As MPC is being embraced by the industry despite the high implementations costs is due to the fact that they get return on investments under 18 months. Hill (2011) questions this wide spread acceptance of MPC by the industry. He argues that the advanced regulatory control may be better suited than MPC for certain processes in petrochemical industries.

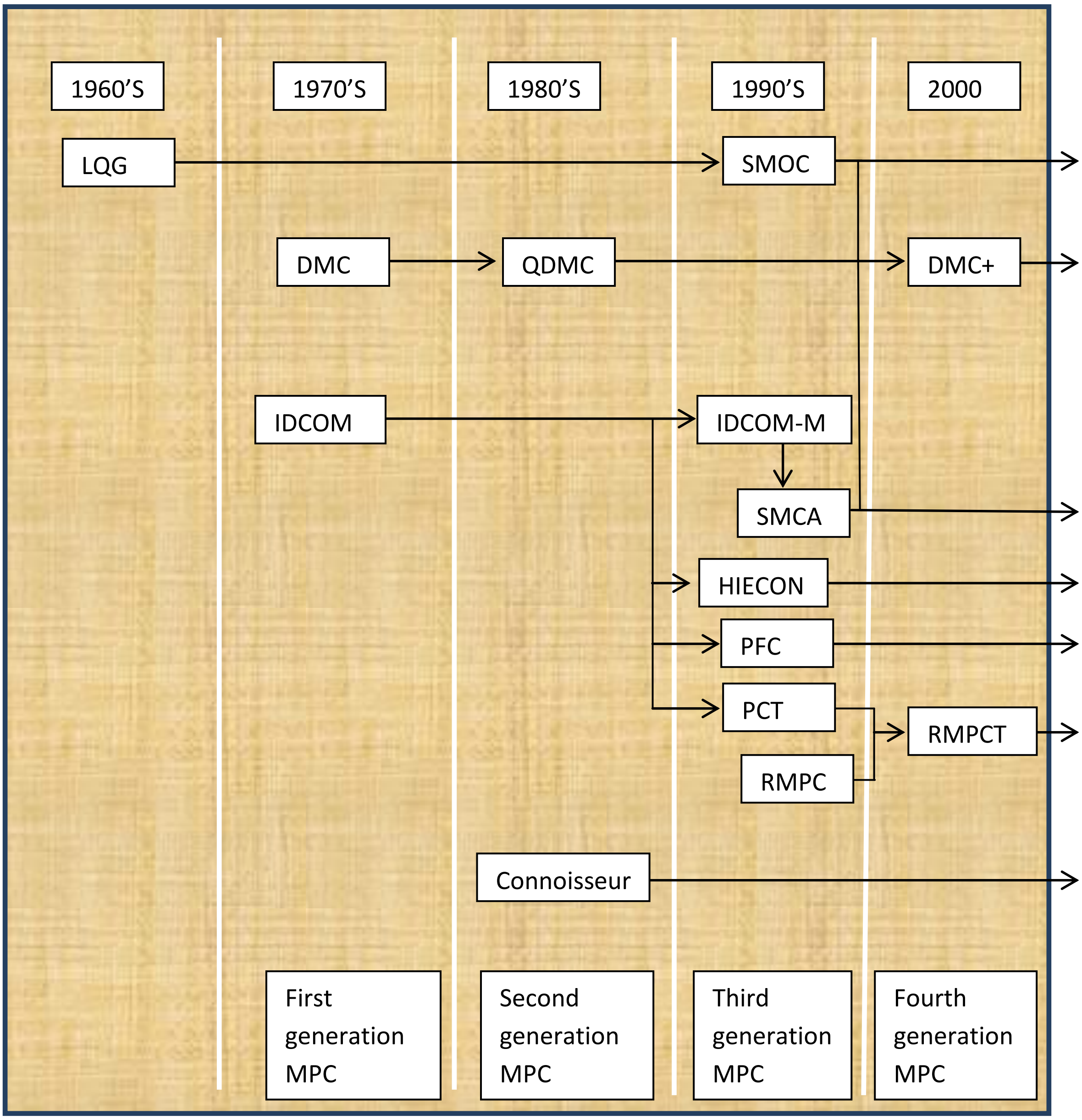

Figure 3: Approximate genealogy of linear MPC algorithms

6.1 Important concepts in MPC

As noted above, the success MPC is enjoying is attributed to the fact that it was developed in the industry, by the industry and for the industry. A good account of MPC technology from the past to the future has been reviewed by Morari and Lee (1999) while a comparison between both theoretical and practical aspects of MPC has been undertaken by Carlos et al., (1989).

The process output is predicted by using a model of the process to be controlled. Any model that describes the relationship between the input and the output of the process can be used. Further if the process is subject to disturbances, a disturbance or noise model can be added to the process model. In order to define how well the predicted process output tracks the reference trajectory, a criterion function is used. Typically the criterion is the difference between the predicted process output and the desired reference trajectory. A simple criterion function is,

$$J = \sum_{i=1}^{H_p} [\hat{y}(k+i) - w(k+i)]^2 \tag{9}$$

where $\hat{y}$ is the predicted process output, w is the reference trajectory, and H_p is the prediction horizon or output horizon. The general structure of an MPC is shown in the following figure 4.

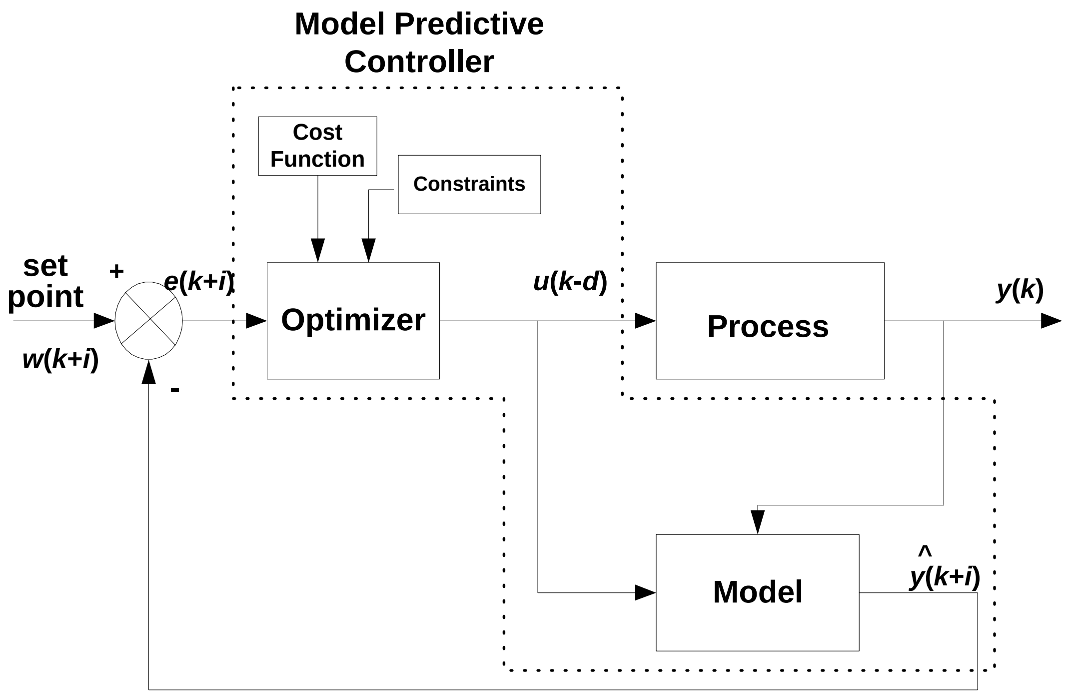

Figure 4: General structure of a model predictive controller

The optimal controller output sequence *uopt* over the prediction horizon is obtained by minimisation of J with respect to u. As a result the future tracking error is minimised. If there is no model mismatch i.e. the model is identical to the process and there are no disturbances and constraints, the process will track the reference trajectory exactly on the sampling instants.

The MPC algorithm consists of the following three steps.

Step 1. Use a model explicitly to predict the process output along a future time horizon (Prediction Horizon).

Step 2. Calculate a control sequence along a future time horizon (Control Horizon, H_c), to optimize a performance index.

Step 3. Employ a receding horizon strategy so that at each instant the horizon is moved towards the future, which involves the application of the first control signal of the sequence calculated at each step. The strategy is illustrated as shown in figure 5.

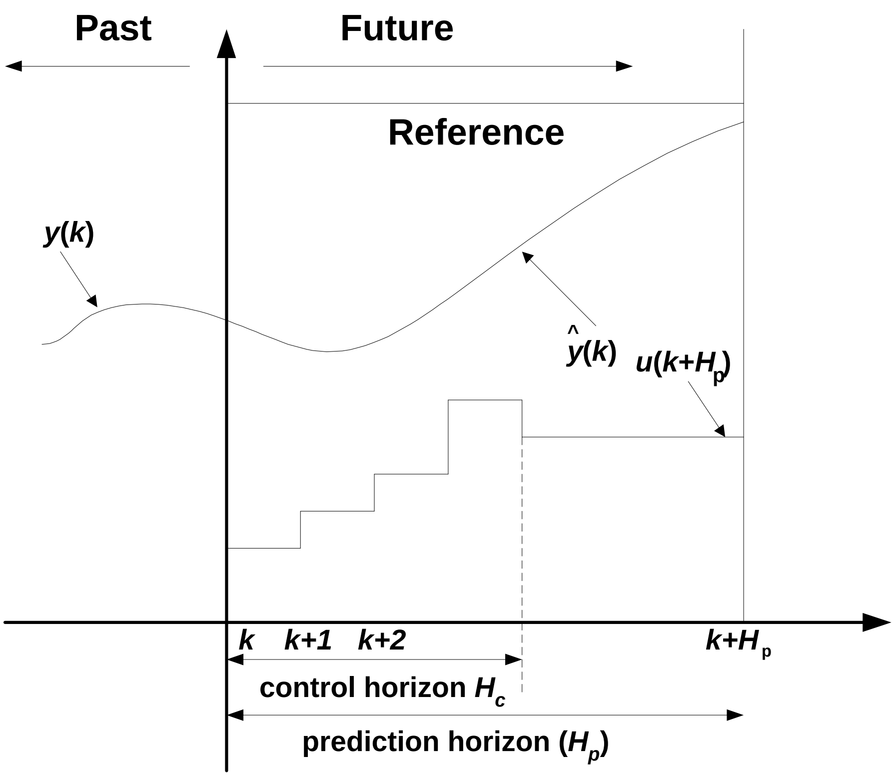

Figure 5: General strategy of a model predictive controller

In the above figure 5, the predicted output and the corresponding optimum input over a horizon Hp, where u(k) is the optimum input, ŷ(k) is the predicted output, and y(k), process output.

The selection of MPC to control a USV is attributed to several factors. Some of them are listed below;

- The concept is equally applicable to single-input, single-output (SISO) as well as multi-input, multi-output systems (MIMO).
- MPC can be applied to linear and nonlinear systems.
- It can handle constraints in a systematic way during the controller design.

The controller is not fixed and is designed at every sampling instant based on actual sensor measurements so disturbances can easily be dealt with as compared to fixed gain controllers.

6.1.1 Model predictive control overview

Morari and Lee (1999) present a good overview of the MPC. Zanovello and Budman (1999) presents a MPC algorithm with soft constraints. FNWMPC (finite number of weights model predictive control) based on selecting proper combination of weights when constraints are violated. Mayne, et al., (2000) deal with the stability and optimality of MPC.

6.1.2 Linear programming and model predictive control

MPC is partially limited by the ability to solve optimization problems in real time. One strategy for improving the computational performance is to formulate MPC using a linear program. While the linear programming formulation seems appealing from a numerical standpoint, the controller does not necessarily yield good closed-loop performance. Also, Qin and Badgwell (2003) provide a good overview on MPC as well. A combination of penalties on moves, reference trajectory and model filter was used to tune the MPC in a practical way by Wojsznis, et al., (2003).

6.1.3 Genetic algorithm based model predictive control autopilot

A genetic algorithm based (GA-MPC) was designed and applied to an AUV is presented by Naeem, et al., (2005). It is the first known application of an online GA operating in an underwater vehicle in real time. Also, linear quadratic Gaussian (LQG) controllers were designed and tested with the electric trolling motor. These controllers demonstrated excellent line-tracking performance, with error standard deviations of less than 0.15m. The wing-sail propulsion system was fitted, and these same controllers re-tested with the wing providing all propulsive thrust. Line-following performance and disturbance rejection were excellent, with the cross-track error standard deviations of approximately 0.30m, in spite of wind speed variations of over 50% of nominal value (Elkaim, 2009). The controller is able to achieve good performance due to the accurate modelling of the system in discussion.

6.1.4 Convex and nonconvex optimization problem

Linear MPC is pretty much a convex optimization problem and stable results are available. However, for non-linear MPC optimization problem is more complicated and is in general non-convex. This means that the global optimality cannot be guaranteed (Åkesson and Slätteke, 2006). The solution of the optimization problem provides the feedback control action, and can be either computed by embedding a numerical solver in the real-time control code, or pre-computed off-line and evaluated through a lookup table of linear feedback gains (Bemporad, 2006).

Fuzzy reasoning techniques and neural network structures are applied to MPC by Tatjewski and Lawrynczuk (2006). The two components of the most commonly used quadratic cost functions in MPC are given by the following equation (10) .

$$J(k) = \sum_{p=N1}^{N} ||y^{sp}(k+p|k) - y(k+p|k)||^2 + \lambda \sum_{p=0}^{N_u-1} ||\Delta\, u(k+p|k)||^2 \tag{10}$$

where $y^{sp}(k+p|k)$ is the set point and $y(k+p|k)$ is the predicted output. N_u is control horizon and it must satisfy the it must satisfy the constraints $0 < N_u \leq N$. The vector of control increments is represented by $\Delta\, u(k+p|k)$ and λ is the coefficient to scale the sum of squared control increments. The optimal control trajectory is calculated at each sampling instant by minimising the above cost function. The predicted controller outputs are calculated by using the following generalised input-output process model (11).

$$\begin{aligned} y(k+p|k) = f_p\,(u(k+p-1|k), \ldots, u(k|k), u(k-1), \ldots, u(k-n_B), y(k), \\ y(k-1), \ldots, y(k-n_A), d(k), p = 1, \ldots, N. \end{aligned} \tag{11}$$

Nonlinear models result in nonquadratic, nonconvex optimisation problems. Hence the online computation of the MPC algorithm encounters a major problem. Furthermore improvements due to application of neural networks in modelling are also illustrated by Tatjewski and Lawrynczuk (2006).

6.1.5 Analytical performance prediction for robust constrained MPC

Richards, et al., (2006) offers a completely different perspective to solve the MPC control problem. This paper presents a new analysis tool for predicting the closed-loop performance of a robust constrained model predictive control (MPC) scheme. Most other methods use computationally expensive numerical simulations to investigate the effect of controller parameters like the horizon length, cost of weightings and constraint settings. The computational burden is avoided by analytic method. The expected performance of the controller was predicted using a combination of gains of 2 linear systems, the optimal control for the unconstrained system and a candidate policy used in performing the constraint tightening. Also, the mismatch between the predicted level of disturbance and the actual disturbance encountered by the system in real time is taken care of in this method.

6.1.6 Linear systems controller design via convex invariant sets

Sui and Ong (2008) presents two control strategies under the time optimal control (TOC) and model predictive control (MPC) frameworks for constrained piecewise linear systems with bounded disturbances (PWLBD systems). Each of the proposed approaches uses an inner convex polytopal approximation of the non-convex domains of attraction and results in simplified control laws which can be determined off-line via multi-parametric programming. These control strategies rely on invariant sets of PWLBD systems. Thereby, approaches for the computation of the disturbance invariant outer bounds of the minimal disturbance invariant set, and convex polytopal disturbance invariant sets are presented.

6.1.7 Dynamic model predictive control

Martensson and Wernrud (2008) overcomes the optimal control problem of MPC by proposing to parameterize the control sequence in each sampling instant a dynamic feedback compensator is computed. Hence the control system runs in a closed loop when the computational delays are present. Whereas, in traditional MPC a finite horizon open loop optimal control problem is solved at each sampling instance which might lead to problems if uncertainties are present.

6.1.8 Fast model predictive control using online optimization

MPC has slower dynamics and is well suited for process industries. When the plant to be controlled is an USV like *Springer* the system dynamics tend to be faster (depending on the operational mode and mission desired). Fast MPC computes the entire control law offline and hence reduces the online controller to a mere look up table. This method works well for system with small state and input dimensions. Fast MPC can compute control actions 100 times faster than generic optimizers (Wang and Boyd, 2010). An example problem with 12 states, 30 prediction horizon, and 3 control horizon is solved in less than 5msec (hence MPC be carried out at 200 Hz). It is worth noting that currently MPC used in *Springer* USV operates at 1 Hz. The need to solve an optimization problem at each step leads Mattingley, et al., (2010) to wonder if MPC is only suitable for systems with slow sampling. Different authors attempt to solve this problem by different approaches. Explicit MPC is one such approach where in the problem is solved analytically and explicitly. Hence the control policy involves only searching through a lookup table. Another approach is to solve the optimization problem efficiently by hand written code. However, drawbacks include substantial development time, specialised knowledge of optimization and numerical algorithms. The authors in this work have benefited greatly from the developments in the field of convex optimization code generation. The MPC policy is specified in a high-level language and the source code is generated for a custom solver. The custom solver is much faster than generic solvers. This enables the user to utilize MPC polices at KHz rates.

6.1.9 Real time optimization with model predictive control

A continuous systems real time optimization (RTO) has been integrated into MPC by one layer strategy by De Souza, et al., (2010). The cost function of the controller contains the gradient of the economic objective function. Non-linear process model has been used to obtain the optimal conditions of the process at steady state. The plant step test has been used to obtain the linear dynamic model and this linear model has been used to obtain the trajectory to be followed. A quadratic programming routine is used at each sampling step to solve the resulting control / optimization problem. This approach provides equivalent results instead of solving the entire optimization problem inside the MPC controller. Solving the full economic optimization inside the MPC controller results in a non-linear programming problem where the computational power required is much greater.

6.1.10 Feed forward model predictive control

Preview action is used as a standard in MPC. However, feed forward which is rarely used in the formulation of MPC provides significant improvement when there is an uncertainty with the model and measured noises are presented by Carrasco and Goodwin (2011).

6.1.11 Distributed model predictive control algorithm

The model is decomposed into N subsystems. Time-varying state-feedback controller has been used for each subsystem to solve the N convex optimization problem. This has been incorporated into an online algorithm which addresses the problem with model errors in DMPC (distributed model predictive control) (Liu, et al., 2011). The data from MPC vendors have been collected by Liu, et al (2011) to provide an overview of linear and nonlinear MPC available in the market currently. It also provides a good summary of identification technology and MPC applications available in the market commercially.

MPC has been combined with an adaptive input disturbance predictor to solve the problem faced by ships which travel in high seas(Liu,et al., 2011). Traditional stabilization systems performance declines due to the uncertainties in the hydrodynamics as a result of change in sailing conditions and sea states. An autoregressive model of the input disturbance has been used to predict the wave disturbance and the MPC is used to compensate this predicted disturbance. This combination helps the control system to deal with mode uncertainties with robustness. It also enables the ship to adapt to changing sea conditions. This combination solves the problem of performance degradation resulting from state observer estimation errors. Generally the state observers are used with the MPC to estimate output distances. (Liu,et al 2011).

6.1.12 Subspace methods in MPC

Subspace methods were used by Privara, et al., (2011) to obtain the MIMO (multiple input multiple output) model of the building heating system to design an MPC controller.

6.1.13 Autonomous vehicles control using MPC

The accurate control of the autonomous vehicle can be obtained efficiently by using MPC (Kim, et al., 2004). Ghaemi, et al., (2010) presents the experimental implementation of MPC strategy for path following on a model ship. The MPC is designed and implemented using both linearized and nonlinear model. The experimental test results from *Springer* USV with modified optimal controller show promising results amidst external disturbances and uncertain models Naeem, et al., (2012). Soft computing methodologies have also been used to develop the subsystems algorithms. A fuzzy LQG autopilot for *Springer* USV was found to perform better than standard LQG and GA-MPC autopilots (Naeem, et al., 2012).

6.2 Nonlinear MPC

Linear MPC has been popular since 1970s and the nonlinear MPC (NMPC) has been popular since 1990s among the control theorists. The basic principles of NMPC have been reviewed along with the major benefits and drawbacks of NMPC have been discussed in this section.

6.2.1 Nonlinear predictive control techniques using neural network models

General constrained nonlinear optimization problem has been transformed into convex optimization problem by Botto and Costa (1998). The authors had proposed two techniques to achieve the same objective. The first method uses a linearization through a Taylor's expansion of an affine neural network prediction model. The second method uses the same affine neural network model in a feedback linearization scheme. It was found that both strategies handle model/plant mismatches well but the Taylor's expansion of the nonlinear model affected the performance of the overall closed-loop. Hence, the authors recommend the use of linear model-based predictive control (MBPC) with feedback linearization over the Taylor's expansion method.

6.2.2 A Quasi-infinite horizon NMPC scheme with guaranteed stability

Asymptotic closed loop stability is guaranteed by NMPC (Chen and Allgower,1998). An integral square error (ISE) forms the objective function that needs to be minimized. When the Jacobian linearization of the nonlinear system to be controlled is stabilized, the open-loop optimal control problem of the closed-loop system is asymptotically stable. The challenge of controlling a nonlinear process was achieved by using NMPC by Piche, et, al (2000)

6.2.3 Integrated partial least square and neural network

Aspen technology Inc., developed an NMPC where the control problem is solved at each control step interval. Li and Biegler (1989) and Oliveira and Biegler (1995) propose a multi-step Newton type algorithm to calculate the control output in a cost-effective manner. A NN is connected in parallel to the linear MPC output and this hybrid model is flexible to combine the linear and nonlinear models. In NN training partial least square (PLS) algorithm is used to ensure robust identification. The NMPC is applied to two example control problems; pH control of a two-tank continuous stirring tank reactor (CSTR) neutralization system and application to a pulverized coal-fired boiler to demonstrate the ability of the controller (Zhao, et al., 2001).

6.2.4 Genetic algorithm for nonlinear model predictive control

A multi-layer perceptron NN was chosen to model an UUV named *Hammerhead*. The obtained model was used to implement a GA- NMPC and the results were verified experimentally by Naeem, et al., (2005). The GA-NMPC autopilot was able to perform two waypoint following scenarios.

6.2.5 Nonlinear model predictive control using deterministic global optimization

Local optimization techniques make the system to be vulnerable to suboptimal solutions. The problem gets compounded as a nonlinear non-convex problem needs to be solved at each iteration. This is overcome by utilizing the deterministic global solution techniques. However the problem with this approach is the increase in the computational load (Long, et al., 2006).

6.2.6 Vehicle lateral stability using set membership predictive control techniques

A NMPC has been used to model system nonlinearities and the input constraints to control the yaw of a vehicle by Canale, et al.,(2010a). Nonlinear Set Membership (NSM) methodology has been used to obtain a nonlinear model of the vehicle to be used by the NMPC. Additionally, the NSM techniques incorporate the model uncertainties and enable the stability analysis of the closed loop system to be performed as well.

6.2.7 Efficient MPC for nonlinear systems via function approximation techniques

NMPC is implemented by using approximated control laws by Canale, et al., (2010b). Closed loop stability performance and its relation to the accuracy properties of the generic approximated controller are discussed in detail in this work.

6.2.8 Hardware neural networks

Hardware neural networks (HNN) used to realize NN are covered comprehensively by Misra and Saha (2010). Complete NN models have been realized as neurochips (based on digital, analog, hybrid and field-programmable gate array (FPGA) approaches). HNN are very helpful to realise the system in reality. Implementation through reconfigurable FPGAs has been discussed in detail in this paper. Another possibility is to use adaptive neuro-fuzzy inference systems (ANFIS). Craven (1999) has done extensive work in this area. He exploited Jang's (1992) approach to novel fuzzy inference system and developed multivariable co-active ANFIS (CANFIS) type structure and a new Gaussian inference control algorithm and architecture. Nevertheless, the study is heavily focused on mathematical analysis and simulations results. As rightly pointed out by Roberts (2008), superior performance in simulation studies do not directly translate to improvement of efficiency or performance in reality. Additionally stability issues have also been reported. Hence this approach will not be investigated any further as current developments in *Springer* are focussed on improving the system performance in a practical way under real life conditions.

6.2.9 Neurodynamic optimization approach to NMPC

Recurrent neural network (RNN) has been successfully utilized in NMPC by Pan and Wang (2010). The NMPC optimization problem is reformulated as quadratic programming problem with unknown parameters which is solved by using RNN. Global convergence and low complexity are some of the main advantages of employing RNN.

6.2.10 Real time nonlinear model predictive control for fast systems

Another approach to obtain the NMPC for fast systems is by developing the same number of linear models as the prediction horizon along a desired trajectory at each instant. This approach reduces the NMPC problem into a linear quadratic optimisation problem (Rahideh and Shaheed, 2010).

6.2.11 Fuzzy wavelet network based controller for nonlinear systems

A controller has been designed for nonlinear systems by using an adaptive variable structure fuzzy wavelet network by Hussain, et al., (2007). The advantages of sliding mode control and the fuzzy wavelet networks have been combined to form a new controller capable of handling the nonlinear systems. The fuzzy wavelet network is used to produce an approximate control signal of the nonlinear function. Fast convergence of the fuzzy wavelet network is its key strength. A variable sliding surface assists in decreasing the errors due to approximation and external disturbance. This combination of the control exhibited robust closed loop performance. A simulation example is presented to illustrate the efficiency of the proposed approach.

6.3 Concepts of multiparameteric programming

Programs dependant on only one scalar parameter is referred to as parametric programs. The problem dependants on vector of parameters are classified as multiparametric programs.

There are three main algorithms are :

1. multiparametric linear programs (mp-LP),

2. multiparametric quadratic programs (mp-QP) and
3. multiparametric mixed integer

Parametric programs divide the space of parameters into distinct regions which represent the respective performance of as a function of uncertain parameters. This enables the decision making process to have a complete map of different possible outcomes. Thus parametric program is immune to uncertainties unlike mathematical programs.

Zadeh and Whalen (1962) were the first to express an optimal control problem for constrained discrete time linear systems as a linear program. The multiparametric program enables one to compute the solution to an optimal control problem explicitly as a function of the initial state. Since 1960's the process automation has changed considerably due to the introduction of MPC and it has become very popular for automatic regulation of process unit. However, MPC imposes severe computational burden inherently. In a MPC, an optimization problem needs to be solved online in order to compute the next command action. Additionally, current sensor measurements influence the optimization problem as well. Computational burden can be removed by solving the multiparametric programs offline and the command inputs are the optimization variables and the measurements are the parameters. Gass and Saaty (1955) proposed the first method for solving parametric linear programs. The concept of critical region is utilised by multiparametric analysis. A critical region is a set of parameters space where the local conditions for optimality remain unchanged for a given parametric program.

6.3.1 Multi-parametric programming approach for dynamic programming problems

Dynamic and multi-parametric programming techniques have been utilised by Faísca, et al., (2007) to solve multi-stage optimization problems. To solve this problem, the present states and the future decision variable are parameters and the optimization variables are obtained by present decision variables. This rearrange of the original problem reduces it to a set of lower dimensional multi-parametric programs that can be solved sequentially. Analytical nonlinear function is approximated by affine functions which are valid in confined regions of optimality and feasibility. The solution obtained is continuous and convex.

6.3.2 Linear model predictive control via multiparametric programming

Linear MPC optimization problem is solved by using a multiparametric quadratic programming with quadratic objectives and linear output and input constraints. Thus a complete map of the optimal control is obtained as a function of states and properties of the partitions of the state space. Hence, the MPC problem is obtained as piecewise affine feedback control law. The optimizer is never called online. Instead, measurements of the states are obtained and number of linear inequalities and linear affine functions provide the control action required. Thus online computational burden is greatly reduced as the optimization problem is solved offline by the parametric optimization concept (Sakizlis, et al., 2007).

6.4 Multivariable MPC

Model uncertainties and signal uncertainties are create sensitivity of the system. This sensitivity is greatly reduced by changing the dynamics of the system by providing a feedback. This generally makes the system faster and sufficiently stable. Asymptotic method (ASYM) of identification is used for multivariable process identification for model based control (Zhu, 1998). The frequency domain criterion is used to calculate the time domain parametric models in this method.

Multivariable MPC and closed loop identification are presented by (Zhu, 1998). ASYM is used for identification and the main problems are dealt with in the following order in a systematic manner:

1. test signal design for control

2. model order/structure selection
3. parameter estimation and
4. model validation

An accurate input/output model and unmeasured disturbance model, model errors are quantified by an upper error bound matrix that can be used for model validation and test redesign in this method (Zhu, 1998).

Jiang, et al (2006), present methods to detect and isolate model-plant mismatch for multivariate dynamic systems. These methods estimate process model parameters from both open and closed loop step responses. Model parameters are estimated from single step test. Estimation equations are developed in terms of absolute values of variables as opposed to their deviational values. This facilitates direct use of industrial data without pre-processing. A new scheme to detect model plant mismatch (MPM) for the multivariate dynamic systems and three MPM detection indices are defined by Jiang, et al (2007)

The assessment and diagnosis procedures are integrated to obtain a system used to monitor the performance of multivariable MPC by Tian, et al., (2011). The monitored variable set contains the model predictive error and 2 –norm based covariance benchmark is presented by the authors. The Performance of the MPC is evaluated by comparing the actual data with the 'golden' user-predefine one. The similarity between the current data set and the established classes is incorporated into the eigenvector angle. When the performance of the MPC degrades, it is identified by and an angle-based classifier.

7. CLOSED LOOP SYSTEM IDENTIFICATION

The purpose of closed loop system identification (CLID) is to identify a mathematical model while the plant is under feedback control. CLID is preferred for economic reasons as it :

- is less disruptive to normal plant function.
- provides an opportunity for online auto tuning of the control system.

Another advantage is that the controlled variable of the system does not drift while performing CLID. The above figure 6 illustrates the concept of SISO closed loop system identification. A pseudo random binary signal is used to excite the system.

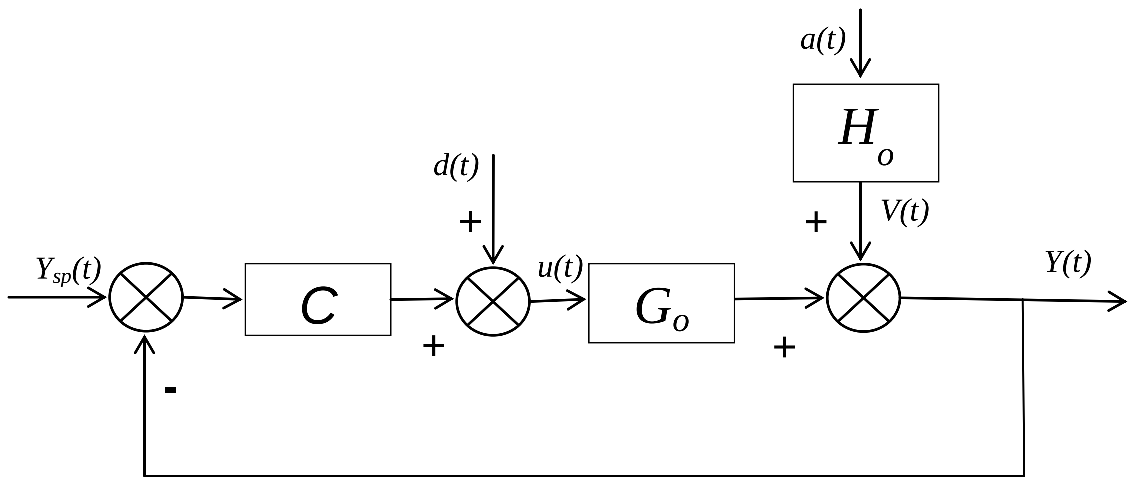

Figure 6: Closed loop system identification

SI in closed loop is presented by Landau and Rolland (1994). The convergence analysis of the parameter estimation algorithm is presented by the authors in this work whereas the effects of a model developed by approximate identification under closed-loop and the model-based control design are presented by Hof and Schrama (1995). Moreover, closed-loop identification gives better performance for model-based control design (Hjalmarsson, et al., 1996). The controller performance is measured as the variance of error between the output of ideal and actual closed loop system. When the controller is a smooth function of the input-output dynamics and the disturbance spectrum, the best controller performance is achieved by performing the identification in closed loop with an operating controller.

The closed-loop system must be stable but it is allowed to be unstable in open-loop. Tontiruttananon and Tugnait (1998) proposed two identification algorithms using cyclic-spectral analysis of noisy input-output data. The open-loop transfer function is first estimated using the cyclic-spectrum and cyclic cross-spectrum of the input-output data. These transfer function estimates are then used as "data" for the algorithms investigated by the authors. Computer simulation examples are presented to support the proposed approaches.

7.1 Comparison of the closed-loop identification methods

A good overview of different closed-loop identification methods such as classical method, 2-step identification and closed-loop output error algorithms are presented by Karimi and Dorã (1998). Bias distribution of the estimates is used to compare the different methods. Furthermore, closed loop output error identification method has been illustrated by Karimi and Dorã (1998).

The common framework is created by the basic prediction error method, and it is shown that most of the common methods correspond to different parameterizations of the dynamics and noise models. The so-called *indirect methods*, e.g., are indeed “direct" methods employing noise models that contain the regulator. Classification of CLID techniques are based on different assumptions of feedback configuration and it can be summarized as in the following figure 7.

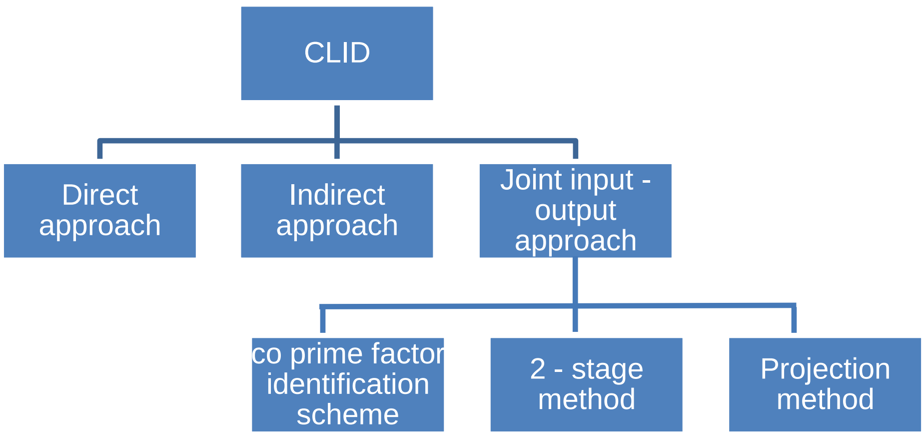

Figure 7: classification of different CLID techniques

7.2 From robust control to adaptive control

Interaction between adaptive control, identification in closed loops and robust control are explored by Landau (1999). The performance of the control system is enhanced by using multiple-model adaptive control based on switching and tuning. Asymptotic and finite data behaviour of some closed-loop identification methods are presented by this author. Closed-loop identification can generally identify models with smaller variance than open-loop identification.

7.3 Closed-loop system identification via a tailor-made IV method

A bias-correction method for closed-loop identification, introduced in the literature as the bias-eliminated least squares (BELS) method is presented by Hof and Gilson (2001). This is referred to as the tailor-made IV method for closed-loop identification.

7.4 Closed loop identification with auto-tuning

A robust closed-loop identification method is presented by de Klerk and Craig (2002). A new PID tuning rule is used to construct the auto-tuner. The process frequency response is obtained by using fast Fourier transform (FFT) and the inverse FFT is used to obtain the process step response. A simulation concerning the closed-loop system identification of a multivariable plant model, where the plant is controlled by a MPC controller, is discussed. A motivation for closed-loop system identification in this context is given. The identification methodology is further discussed and evaluated (de Klerk and Craig, 2002). Advantages of closed-loop identification are discussed and an MPC is designed by utilising the multivariable and closed-loop identification of industrial processes in this paper.

Some main issues regarding closed-loop system identification are reiterated by de Klerk and Craig (2004). A model obtained from open-loop data is used as a reference to evaluate the closed-loop system identification approach.

Wang and Sutton (2005) modelled a remotely operated underwater vehicle by using two stage closed loop system identification (CLID). PID controller is used to control the vehicle and a pseudo random binary signal (PRBS) is used to excite the system. Controlled variable of the system does not drift while performing CLID and it also provides an opportunity for online auto tuning of the autopilot. Zhao and Kearney (2007) provide a similar view regarding tailor made IV method for closed loop identification. However, the ”Hansen Scheme” takes a different approach and utilises dual Youla-Kucera parameterisation of all systems stabilised by a given linear controller to transform the closed-loop system identification problems into open-loop-like problems(Bendtsen, et al., 2008).

Sotomayor, et al., (2009) deal with a procedure of model re-identification of a process under closed loop with an existing commercial MPC. Basically it is a simulation study of two processes in oil refining industry. Traditionally CLID has been used extensively by the petrochemical and process industries. However, there has not been a lot of research in this area. Hence it is worthy to investigate the application of CLID to USVs.

8. CLOSED LOOP PERFORMANCE ASSESSMENT

Closed loop performance assessment is well established in petrochemical and refining industries. Desborough and Harris, (1992) explain how prediction horizon parameter in CLPA algorithm can be used to analyse persistent signals which degrade performance. Refinery applications default values have been established in the literature.

8.1 Spectral envelope

Oscillations are common in many plant-wide processes and it impacts the performance of the overall plant. Hence it is essential to detect and diagnose oscillations at an early stage. There are many techniques to achieve this and spectral envelope is one such technique. The variables causing common oscillations are identified by scaling and power plots (Thornhill, et al., 1998). Thus the root cause variable can be identified and the problem can be rectified. CLPA algorithm requires several parameters to be tuned accurately to achieve optimum results. Procedures for selecting such parameters are described by Thornhill, et al (1999).

8.2 Web-based performance assessment tool

Micheal and Cox (2003) present the case study of Eastman Chemical Company where CLPA algorithm is designed for 14,000 PID controllers in 40 plants based in 9 sites worldwide. Controllers are categorised based on their performance. Historical improvements or degradation of performance of a single controller or an entire plant can be tracked. Automatic emails are generated and the relevant users are kept informed. Controller optimization and productivity has been increased by this system.

8.3 Tree mapping

Petrochemical refineries, paper manufacturing and mining industries have relied upon CLPA as a corner stone of operational excellence (O'Connor and O' Dwyer, 2004). In these industries, CLPA has become mainstream and it is changing the predictive maintenance methodology to condition based methodology to control assets. Due to the inherent sheer size of the operations of the refinery plants, the control problems are more challenging and identifying problems become more difficult. This problem is solved by a data visualization technology called tree mapping. It was initially proposed in 1990s and has been proved to work well in a condition based maintenance framework. O'Connor and O' Dwyer (2004) have applied the tree mapping to CLPA. For further information about regulatory and advanced control examples the reader is directed to O'Connor and O' Dwyer (2004).

8.4 Classification of Methods

An overview of number of controller performance assessment techniques is presented by O'Connor and O' Dwyer (2004). The techniques discussed are divided into five categories, namely, time domain assessment, frequency domain assessment, minimum variance control (MVC) as a benchmark, statistical analysis, and other more 'problem specific' assessment techniques. Recent work, in each of the five categories is outlined in this paper. Furthermore, the CLPA using a MPC benchmark are discussed in detail by Julien, et al (2004).

To get a useful historical perspective from performance monitoring, several key items must be established. Loop health must be defined in terms of performance metrics and then a method for combining these metrics in a useful way must be set up. The first step is for the plant to choose the metrics that will make up loop health. This may vary somewhat depending on the loop type. Once these metrics are chosen, a method for combining the metrics to arrive at a single health number must be decided. This method defines the baseline of performance for every loop. Different categories of loops will have a different basis for performance.

9. CONCLUSION

The background theory and recent developments in the field of USV, SI, MPC, CLID and CLPA have been presented. Furthermore, this section identifies the missing elements in the current literature on the aforementioned topics and provides an opportunity to investigate the following approaches with particular regards to the *Springer* USV.

System overview and different guidance strategies were presented in section 2 and it is clear that waypoint guidance by LOS is the most suitable guidance strategy for *Springer*. Trends in marine control systems and development of USVs were presented in section 3.

Rigid body modelling approach to obtain a model of the operating vehicle was presented in section 4 and section 5 established that SI is a suitable method to obtain an appropriate model to be used in the controller design. MPC history, development and important concepts were presented in section 6. Fast dynamics of the USV imposes the requirement for fast sampling, which has implications with regards to there being insufficient computational time to perform the on-line optimisation. Fast MPC and subspace optimization has not been used in USVs. This is a worthwhile option to reconnoitre. Also, RNN and fuzzy wavelets could be used in NMPC and tested in real time on *Springer*. This approach has not yet been verified experimentally for USVs. The various methods to perform CLID such as the classical method, 2-stage identification, closed-loop output error algorithms, tailor-made IV method and Hansen scheme have been presented in section 7. CLID is traditionally used in process industries and has not been applied to USVs in the literature. Two-stage method appears to be a suitable method to perform CLID on *Springer*. From section 8, it is clear that spectral envelope is used to detect and diagnose oscillations at an early stage in CLPA. Spectral envelope has not been used in USVs to enhance CLPA. Spectral envelope could be used on *Springer* USV to enhance CLPA. This could be investigated further.

The fundamental blocks / subsystems of the autopilot were discussed in detail individually and various areas for improvement were identified. Once all these suggestions are incorporated it will produce a novel innovative autopilot which will be a combination of model predictive control (MPC), closed loop system identification (CLID) and closed loop performance assessment (CLPA). The successful adaptive autopilot subsystem will be integrated into the new advanced intelligent integrated navigation and autopilot system with adaptive capabilities for USVs and will serve as a paradigm for design and development of USV autopilots.

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