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Model Predictive Control: A Summary of Industrial Challenges and Tuning Techniques

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Abstract

This paper provides an overview of industrial challenges and tuning techniques of model predictive control (MPC). For the sake of most of research studies need better algorithms and best tuning techniques to improve their applications performance, several tuning techniques for MPC have been summarized and listed in this paper. A brief description MPC concept is presented first, followed by some industrial applications; strategies based linearity achievement, linear and nonlinear MPC Strategies and MPC tuning techniques formulation. Academic contributions are highlighted and suggestions provided for improving MPC.

Keywords: *Model predictive control, Industrial challenges, MPC tuning techniques, Dynamic matrix control.*

1. Introduction

Since the last decades, the literature of predictive control strategy has grown widely to make a one single comprehensive review. Hence, the references given here are just representatives. This chapter presents a review of previous literature regarding predictive control strategies. Review of tuning predictive control techniques and their related applications in industrial and academic areas are also discussed. Also presented are the concept of MPC and previous mathematical derivation and formulation of the MPC. The basic idea of Model Predictive Control (MPC) is to use a model of plants to predict the future development of the system [1-4]. At every time step, a particular performance index is optimized over a sequence of future input moves that are subjected to operating constraints. The principle point of MPC is to perceive and enhance the important variables at the current time point, as well as through their following tracking path in the future points. Utilizing a heuristic decision of the manipulated variable sequence of the future path, the process variables are computed first. The new manipulated variable sequences are attempted out until the control behavior becomes satisfactory, in case if the future path of the controlled and the constrained variables is not proper yet [5, 6]. There is an essential difference between predictive control and classical PID control. The established PID controller identifies just the present process variables, and the basic scheme of PID controller is not extremely successful for the plant having dead time yet. Nevertheless, the predictive controller monitored the current and the future variables of the plant. The predictive control resulting control law is significant to implement, and although little computation is needed, its derivation is more complex than that of the PID controllers [5, 7]. MPC performance is related to the accuracy of

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identification and the optimal adjustment of the process model [8]. The MPC family controllers are characterized by the following strategy, as represented in Fig. 1. The prediction horizon P is the future output for a decided horizon range, mostly with respect to the settling time of the open loop plant model. The predicted outputs are based on values up to the moment t for the past inputs and outputs. Then, the future control signals are forwarded to the system and calculated.

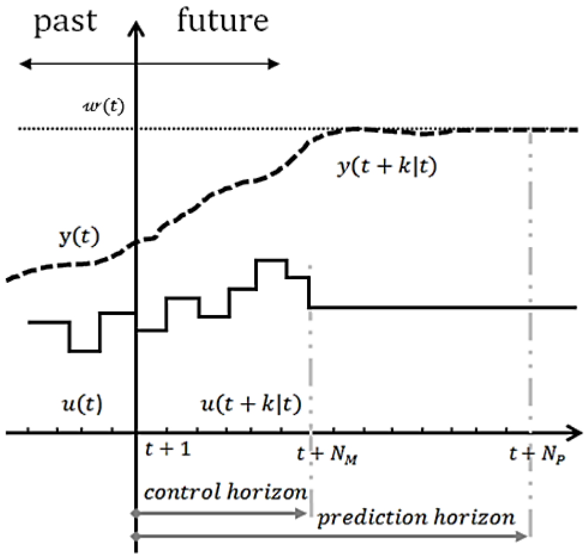

Figure 1: The model predictive control concept.

To keep the process response close to the reference trajectory $w(t+k)$, the pattern of future control response is computed by optimizing a specific criterion. The performance index between the predicted output signal and predicted reference trajectory is the function of this criterion. An iterative optimization technique is needed if the linearity of model is not achieved. Few suppositions about creating the future control law are also considered in some issues, such as that it will be constant from a given instant. The control input signal u(t|t) is forwarded to the process plant, whereas the next control input signals computed are neglected, because the next sampling instant y(t+1) is already calculated. The first shift is iterated with this new value and the sequences are imported up to time response. Therefore, u(t+1|t+1) is calculated which in principle will be different from u(t+1|t) because the new data is obtainable [9, 10].The main features of the MPC are as follows [11, 12]: An accurate predictive model allows us to optimize control inputs for cost over both inputs and predicted future outputs. Such a cost function is often easier and more intuitive to design than completely hand-designing a controller. The prediction of the process model through prediction horizon allows the controller to handle process dynamics directly, such as time delay and lags. Insertion of a state estimator into close loop provides better prediction and improvement of control performance. Consideration of the process behavior and noise over a future prediction horizon help to be minimize the formulation of the cost function to be minimized, thus the feedback disturbance can easily to reduce.

Fig. 2-3 shows the difference between non-predictive and predictive control. Non-Predictive control (like PID control) deals with current, over internal memory, and past data. Meanwhile, the predictive control considers also future reference and/or disturbance and predicted the manipulated inputs and controlled signal sequences. The selector produces the current control signal from the calculated manipulated variable sequences.

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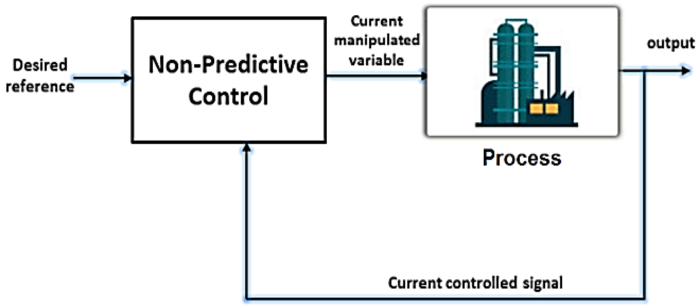

Figure 2: Typical structure of Non-Predictive control block diagram.

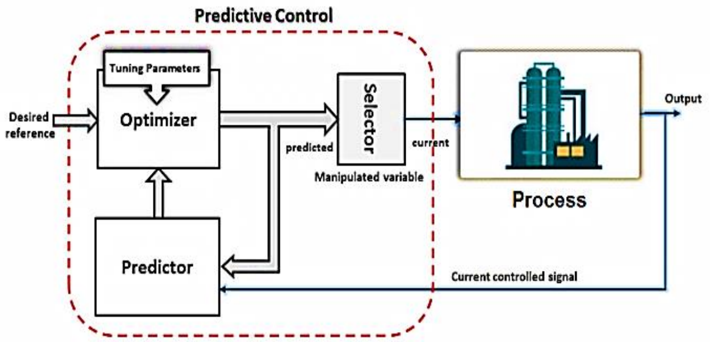

Figure 3: Typical structure of Predictive control block diagram.

2. Industrial Applications of Model Predictive Control Tuning Strategies

MPC technology was developed by Shell Oil and Gas Company in the early 1970s, with an initial application in 1973. Cutler and Ramaker presented details of an unconstrained control algorithm, which they named as dynamic matrix control (DMC) at the 1979 National AIChE meeting [13] and at the 1980 Joint Automatic Control Conference [14]. They adjusted a matrix that was created in the mid-fifties, called as Pseudo inverse matrix [15] by adding diagonal matrix for the control law to enhance the manipulated variable behavior and decrease the ill-condition. DMC has similarities with the model algorithmic control MAC, with difference by having impulse response for the last one. However, DMC is more acceptable by the process engineers due to adoption of the step response model and having less complexity procedures.

Another MPC approach which receives impressive concern is the Generalized Predictive Control (GPC) method that is different from the previous because it is based on Controlled Auto Regressive Integrated Moving Average (CARIMA) model. Many questions are still open for modern research, as will be discussed in the following. A number of review and survey studies concerning MPC irradiate the control engineering field with valuable investigations. Their discussions include the development of MPC technology and their application status, robustness, and tuning strategies. The applications of MPC technology have been applied to over more than 4600 devices and processes, most of them covering industrial fields of petroleum distillates, petrochemical, and polymer [16]. Some studies covered the technical tuning for MPC parameters and performance analysis [2, 3, 16-29]. Furthermore, MPC has much less impact in the other process industries. Performance monitoring of MPC systems is an important topic of current research interest [30].

There are quite a number of researches and applications in the predictive control field of mobile and autonomous robots [31-35]. Electromechanical devices and actuators have been enhanced by predictive strategies in latest years [36-40].

In the existing industrial MPC algorithms, an optimization problem incorporated with models and constraints is best to be solved online. This is because, manually, at each step, it adopts standard programming algorithms for iterations, which results in heavy computation burden and much calculation time. The computation complexity makes MPC only suitable for slow dynamic processes with larger sampling period [16].

Large number of fast dynamic systems in areas, such as aerospace, mechanical, manufacturing, and electrical etc., without high performance computing devices, such standard optimization algorithms is difficult to meet the requirements of real-time computing with small sampling period. Therefore, it failed in scale applications in these fields. Thus, it is necessary to develop high-efficiency MPC algorithms that could preserve constrained optimization characters and is suitable for real time implementation with very small period of time [16]. MPC is now a part of every refinery and chemical processes. In addition, its scope of application continues to extended, to include mechanical and mechatronic systems that require sampling rates that are orders of magnitude faster [17]. MPC has been proposed to optimize issue with minimum computing effort for fast-switching modular multilevel converters. Capacitor voltage and current can be simulated by fast tracking in small sampling time [41]. Therefore, many researches nowadays is aimed to enhance the performance of fast systems that have small sampling period.

3. Linear Model Predictive Control Strategies

In the process industry, MPC applications are restricted the industrial processes of weak nonlinearity, such as refining, petrochemical, etc. For the strong nonlinear industrial processes, such as gas, pulp, paper making etc., the application of MPC is still rare because of two reasons. Firstly, an exact nonlinear process model adopted in NMPC is often difficult, time-consuming, and expensive to obtain. Secondly, for realistic processes, the numerically solved nonlinear constrained optimal control problems in NMPC often become large, while the control action to suppress disturbances or follow set point changes must be fast enough. The computation complexity makes NMPC mostly suitable for slow dynamic processes with larger sampling period [16, 42].

Widespread, a lot of MPC applications depend on the utilization of linear models, but in reality most industrial processes are nonlinear. There are some considerations for that. Basically, the matching and identification of a linear model based on process plant is comparatively easy. Moreover, linear models guarantee perfect trend when the process plant is operated in the neighborhood of the operating point. Besides, the use of a linear model together with a quadratic objective function gives rise to a convex problem, whose solution has been well studied with many commercial products available. MPC of a linear plant with linear constraints gives rise to a nonlinear controller, and this combination of linear dynamics and linear constraints has influence on the commercial success of MPC. Meanwhile, NMPC is used for predictive controllers that make use of a nonlinear dynamic model, and leads to extra complexity [43]. A logical extension of the above is the use of a nonlinear model, given the ubiquitous of nonlinear control problems and the lack of a universally accepted nonlinear control solution. Providing the MPC algorithm for constrained linear to nonlinear systems is theoretically smooth but meets with difficulties for real applications [17].

Most of the stability results for the constrained linear systems can be applied to nonlinear systems without modification. In fact, many of the earlier stability results for constrained optimal control were developed in the context of a general nonlinear system [44-46]. However, the real implementation is strictly difficult due to the computational complexity in finding optimal solution to a non-convex optimization issue.

Worthy article with industrial application presented at AIChE National Meeting Texas [47] described an application of DMC technology to an Fluid Catalytic Cracking Unit (FCCU) reactor/regenerator, in which the algorithm was modified to handle nonlinearities and constraints. The controller was adjusted manually. Moreover, the paper did not discuss their process identification technology [22]. MPC has had a much greater impact on industrial practice than IMC or Smith predictor, because it is more suitable for constrained MIMO control problems [30].

MPC is applied to linear systems by designing terminal state constraints and weights for nominal systems with all states available. Adding suitable terminal state weights and constraints to the original performance measure is a way to enhance the stability. However, this is at the cost of possible loss of feasibility in the optimization. The method uses second order cone programming (SOCP), instead of linear quadratic programing (LQP). This approach targets to design the constraints so that feasibility is improved, compared to the prevailing method. In addition, a method to analyze the actual impact of ellipsoidal terminal state constraints has been developed [48].

A way of achieving the real system is to use an adaptive scheme such as adaptive dynamic matrix control (ADMC). It becomes necessary to estimate the process model, which can identify under open or closed-loop conditions. ADMC is applied to tune when large transitions have been found or disturbances get into the process. ADMC has been developed for closed-loop identification of a process in term of its open-loop step response coefficients. These coefficients are used to update the elements of the dynamic matrix. It is necessary to obtain experimental data over a minimum identification horizon, since the rest of the step response coefficients are predicted from a fitted model. The algorithm has a built-in procedure to automatically identify any large step-like disturbance requiring adaptation of the DMC. The efficacy of the identification scheme has been successfully tested on a distillation column plant. Experiments on a pilot scale distillation column demonstrated effective communication structure as well as vindicating the model results. It is envisaged that the ADMC will be able to overcome the shortcomings of the DMC controller in the face of large process model mismatch, thus improving its robustness in the industrial environment. However, the controller parameters need to be estimated experimentally [49, 50].

In classical control design, robustness is ensured by choosing sufficiently large gain and phase margins from open-loop Bode plots. In modern control design, robustness becomes more complex to ensure, since LQG/MPC designs approaches rely on the observer model. For aggressive tunings, small deviations between the observer model and the process can cause instability or significantly degrade performance. It is possible to detune the system, such that deviations between process and model. The price in doing so is degradation of performance, i.e. the system operates well beyond the theoretical limits [51]. The system's performance and robustness over a wider operational range improved by design of a robust predictive feedback controller with multiple models. The approach is to relate the control law performance to the prediction of performance. The resulting controller identifies, at each sample, the closest linear model to the actual operational point of the controlled system, and reconfigures the control law so that it can ensure robust stability of the closed-loop system. The reconfiguration of the controller is carried out by switching the function used to measure the closed-loop performance and the constraints. This idea implies the combination of multiple models, switching and tuning control with receding horizon control [52]. The robustness can enhance the performance by formulating the MPC in terms of two-degree-of-freedom or Self-Tuning Regulator (STR) controller configuration for SISO linear systems. This facilitates simultaneous exercising of MPC robustness analysis and tuning its parameters to achieve a frequency shaping of the resulting feedback loop. Varying time-delay characteristic has also been investigated. This critical issue has motivated further research studies to explore for proper parameter tuning procedures to fine-tune the closed-loop response for good performance and stability assurance. The weakness of this article is that it did not include investigation with changing in processes parameters, and high controllability ratio is

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needed to ensure the robustness stability and characteristics [53]. MPC tuning problem translated to a frequency domain control design problem to reduce the tuning effort of an unconstrained linear MPC formulation. The obtained suppression coefficient parameter chosen empirically as a very small value. Further theoretical analysis of the loop recovery in presence of constraints and other MPC formulations, remains as future work for their research [54].

Genceli and Nikolaou [55] investigated cases for robust stability and robust performance of DMC systems. The authors considered a norm performance index, a terminal state condition as a stability constraint, and impulse-response model with bounds on the variations of the coefficients. They derived a robustness test in term of simple inequalities to be acceptable and satisfied, because of the effort and hardness caused in case of poor process dynamic.

Most chemical processes are inherently nonlinear. However, because of their simplicity, linear control algorithms have been used for the control of nonlinear processes. The predictive DMC and simplified MPC (SMPC) methods are used to control pH neutralization process. The nonlinearity is handled by dividing the operating region into sub-regions and by switching the controller model as the process moves from one sub-region to another. A simple modification for MPC methods is monitored to handle the switching. Simulation and experimental tracking have demonstrated that the modification MPC can provide comparison to PID control a significant improvement in the control of nonlinear pH neutralization process [56].

Fuzzy weighting method is commonly integrated into the multi-linear model DMC (MDMC) to obtain normalized eigenvalue. The fuzzy weights of local models are calculated using Takagi-Sugeno modeling and a type of nonlinear measures of normalized eigenvalues at different operation points. Multi-model control method is a combination of DMC scheme and Takagi-Sugeno modeling. Local models are designed by step response of the actual plant to generate model bank. Each local model is linear, obtained at the corresponding operation point through step experiments. However, the method is time consuming for the designed rules, but more efficient for monitoring compared to the conventional DMC method [57].

4. Nonlinear Model Predictive Control Strategies

Nonlinear model predictive control (NMPC) is found mostly in chemicals, air/gas, and polymer industries. A Local Model (LM) network represents nonlinear chemical process as a basis for nonlinear DMC. A hybrid strategy used for LM network consists of local linear ARX models to indicate improvements in disturbance and tracking responses. However, LM network representation is limited to ARX models only [58]. Quasi-infinite-horizon nonlinear model predictive control approach (QIHNMPC) proposed by [59] can be used to control FCCU reactor. Achieving the feedback stability is the target of this experiment, whose controller consists of the estimation of infinite horizon prediction. Meanwhile, the finite horizon only calculates the input function during the online case. The control parameters are tuned off-line. A quadratic objective function and local linear close loop are used in their method. The terminal penalty expression can be preferable to be quadratic. Stabilization is then enhanced for the high order FCCU process by the QIHNMPC controller [59-61].

The temperature tracking controlled by NMPC is significantly faster to reach the set point than that of the hybrid model predictive control (HMPC). A comparable performance regarding the recycle mole portion tracking is monitored by both of the controllers NMPC and HMPC, but HMPC gives better tracking in comparison with the NMPC control for the product mole fraction set point change. HMPC also provides a proper compromise between on-line calculation and the closed loop performance for the considered nonlinear processes. The tuning parameters' computation methods for both NMPC strategy and HMPC method however, have not been discussed. Computations tuning of the HMPC controller parameters is still a challenge in enhancing the performance [62].

An automatic differentiation (AD) integrated with NMPC called AD-NMPC algorithm was developed by Cao [63]. Using this technique, Taylor coefficients of the states and the outputs at each sampling instant can be calculated automatically, so that future tracking can be easily predicted. The AD technique offers sensitivities of Taylor coefficients against input signals in a completion way. Subsequently, the optimization automatically turns faster. The AD-NMPC algorithm had been tested on an evaporation case study and a good model fitting for the nonlinear plant was obtained. An enhancement of magnitude in computation speed had been observed in the application studies [64-66]. NMPC of five-stage Evaporator System by Continuous Time Recurrent Neural Networks (CTRNN) has been developed. The control parameters include prediction horizon and control horizons computed online by heuristically tuning. The trained neural network been implemented as the internal prediction model of the NMPC strategy. This algorithm reduces network training time and effective solution compared to the conventional algorithm. Significant enhancement in term of the reference trajectory performance and the disturbance rejection can be achieved by the CTRNN algorithm over an early improved PI control [67]. Recently, AD-NMPC algorithm has been applied to satellite attitude model with magneto torque actuator. The process dynamics were simulated to utilize iterative Taylor model, which had performed accurately and had more efficiently results than traditional ordinary differential equation solvers. The Taylor model was implemented with the NMPC control, because of its enable to a continuously variable sampling period [68].

5. Mathematical modeling of MPC

5.1 Mathematical Formulation of MPC

The foundation of this strategy lies with the formal tuning rules for MPC [69, 70] based on fitting the controller output to measured process variable dynamics at one level of operation with a FOPDT model approximation. A FOPDT model has the form:

$$G(s) = \frac{K\ e^{-t_d s}}{\tau_r\ s+1} \tag{1}$$

Dynamic matrix control (DMC) used here to predict future plant output, based on past and current values and on the proposed optimal future control action. These actions are calculated by the optimizer taking into account the cost function (where future tracking error is considered) as well as the constraints. The optimal control law is achieved as:

$$\Delta\hat{u}(t) = [G^T G + \mathcal{W}]^{-1} G^T e \tag{2}$$

G is the dynamic matrix and $\mathcal{W} = \lambda I$, where λ is the weighting on the control effort. Also, e is the vector of the predicted error.

5.2 Implementation of the Weighting Matrix $\mathcal{W}$

An analytical expression for suppression coefficient λ was derived by [69] based on the assumption that the condition number is 500 which was the upper limit of ill conditioning in the system matrix. Consider a control horizon of M = 6; the weighting matrix $\mathcal{W}_{\text{Cooper}}$ is

$$\mathcal{W}_{\text{Cooper}} = \begin{bmatrix} \lambda & 0 & 0 & 0 & 0 & 0 \\ 0 & \lambda & 0 & 0 & 0 & 0 \\ 0 & 0 & \lambda & 0 & 0 & 0 \\ 0 & 0 & 0 & \lambda & 0 & 0 \\ 0 & 0 & 0 & 0 & \lambda & 0 \\ 0 & 0 & 0 & 0 & 0 & \lambda \end{bmatrix} \tag{3}$$

$$\lambda = \begin{cases} 0 & ; M = 1 \\ \frac{M.K^2}{500}\left(\frac{3.5t_r}{T_s}+2-\frac{M-1}{2}\right); M>1 \end{cases} \tag{4}$$

This tuning method explicit formula for the various parameters based on approximation/simulation of the process dynamics or bounds on where the tuning parameters founded based on parameters of the process dynamics. The tuning guidelines proposed by [69] assume that the actual process is well-represented by a FOPDT approximation.

They proposed a tuning strategy for SISO predictive control that is open-loop stable, including non-square systems. The basis of their tuning method is the condition number of matrix A of the process. Their choice of condition number, 500, was based on the "rule of thumb that the manipulated variable move sizes for a change in set point should not exceed 2-3 times the final change in manipulated variable". Additionally, to derive their equation, they approximated the dynamics of the process via an FOPDT model of the process with zero-order hold. From the demonstrations and the effectiveness of apparent that the tuning formula (4) shows promise indeed for the initial tuning of unconstrained SISO DMC strategy [69]. From this, they arrived at an equation that determines P from the maximum of the various combinations of process input and output. The prediction horizon P is limited and not enough to cover wide range of the open loop settling time of the process. The prediction horizon parameter necessary to be bigger to improve the stability of the feedback response [71, 72]. On the other hand, increasing the prediction horizon P has a robust effect and performance enhancement on the closed-loop response. Therefore, always desirable to increase P because of it is found that for several cases, increasing P achieves a slightly less overshoot with better performance index [73, 74]. However, the advantage of this tuning strategy is directly applicable to other parametric predictive controllers such as generalized predictive control GPC [69, 70].

In 2006 another tuning strategy of MPC implemented by reformulating to the MPC law with another was presented. The formulation of the control strategy begins by introducing a weighting suppression coefficient matrix $\mathcal{W}_{\mathrm{Ayad}}$. The structure of $\mathcal{W}_{\mathrm{Ayad}}$ matrix is designed to have three parameters , R_1, R_2, and λ, for any value of the control horizon $M \geq 3$ [75]. Consider a control horizon of M = 6; the matrix $\mathcal{W}_{\mathrm{Ayad}}$ is

$$\mathcal{W}_{\mathrm{Ayad}} = \begin{bmatrix} 0 & -R_1\lambda & \lambda & -R_1\lambda & \lambda & -R_1\lambda \\ -R_1\lambda & 0 & -R_2\lambda & \lambda & -R_2\lambda & \lambda \\ \lambda & -R_2\lambda & 0 & -R_2\lambda & \lambda & -R_2\lambda \\ -R_1\lambda & \lambda & -R_2\lambda & 0 & -R_2\lambda & \lambda \\ \lambda & -R_2\lambda & \lambda & -R_2\lambda & 0 & -R_2\lambda \\ -R_1\lambda & \lambda & -R_2\lambda & \lambda & -R_2\lambda & 0 \end{bmatrix} \tag{5}$$

The suppression coefficient λ is calculated as Cooper's equation (4), and the tuning parameters R_1, R_2 estimated empirically. The research described the importance of using R_1 to increase the matrix and lower the condition number of the matrix especially in case of small values of λ. These are the poor point for the method, where the P should be large enough to include the steady state effect of all past steady state samples, and the empirical tuning for the parameters R_1, R_2 takes time to be estimated. However, the method does not include for small gain plants and estimated only with limited time delay processes.

In this research, the proposed strategy could affect different type of models of first, second, and high order systems, and give more quality responses compared to the previous studies. Especially for enhance the signal performance in terms of decrease the rise time and eliminate the overshoot. The proposed method depends on the transient response output data. The prediction horizon P was set to a value of 20% higher than the settling time sampling data, and the control horizon was chosen to be $5 \leq M \leq 10$. The proposed matrix depends on the suppression coefficient λ, proposed matrix, and other values created from the open-loop response of the original system.

Assume G as the open-loop step response data of the system model.

$G = [\, g_{i+1} \;\; g_{i+2} \;\; g_{i+3} \;\; g_{i+4} \;\; g_{i+5} \; \cdots\cdots \;\; g_{i+n}]$

Then, the proposed matrix $\mathcal{W}_{SMT}$ becomes as:

$h_{i+1} = g_{i+2} - g_{i+1}$

$h_{i+2} = g_{i+3} - g_{i+2}$

:

$h_{i+n-1} = g_{i+n} - g_{i+n-1}$

The proposed matrix is multiplied by the proposed tuning parameter $\lambda_{p\alpha}$ and defined as:

$$\mathcal{W}_{SMT} = \omega_1 \begin{bmatrix} 1/2\omega_2 & h_{i+1} & h_{i+2} & h_{i+3} & h_{i+4} & h_{i+5} \\ h_{i+1} & 1/2\omega_2 & g_{i+1} & 0 & g_{i+2} & 0 \\ h_{i+2} & g_{i+4} & 1/2\omega_2 & g_{i+2} & 0 & g_{i+3} \\ h_{i+3} & 0 & g_{i+3} & 1/2\omega_2 & g_{i+3} & 0 \\ h_{i+4} & g_{i+3} & 0 & g_{i+2} & 1/2\omega_2 & g_{i+4} \\ h_{i+5} & 0 & g_{i+2} & 0 & g_{i+1} & 1/2\omega_2 \end{bmatrix} \tag{6}$$

where ω_1, ω_2 are adjustable parameters mostly $\omega_1 = \omega_2 \cong 1$ or 2, The effect of $\omega_1 < \omega_2$ decreased the rise time and selected with limited range to avoid the higher value of overshoot or disturbance. Denote the output sampled values as $y_1, y_2, \dots, y_n$,and the input $u_1, u_2, \dots, u_n$. Then, the incremental change in u will be denoted as

$$\Delta u_k = u_k - u_{k-1} \tag{7}$$

The response $y(t)$, to a unit step change in u at $t = 0$ and g_i is step response coefficients, h_i is impulse response coefficients, and the impulse response, $h_i = g_i - g_{i-1}$ [76].

6. Model Predictive Control Tuning Strategies

Tuning of an MPC is normally accomplished based on offline simulation and the actual performance of the online controller. Offline simulation, typically using only the nominal model, is used to specify/verify the steady state behavior (ensuring optimal operation for various constraint scenarios) and to determine, via trial and error, initial tuning values for the dynamic control parameters (controlled variable and manipulated variable weights). In light of more powerful computing capability available today, improvements could be realized by techniques that make use of more simulations, to facilitate tuning in light of expected model errors. Another area to consider is incorporating into simulation the characteristics of unmeasured (stochastic) disturbances that could be obtained from historical data, test data, and/or from the actual controller [26].

In a companion paper at the 1983 meeting, [77] presented a predictive control based on discrete convolution models and Tuning of parameters (prediction horizon P, control horizon M ,and sampling interval, Ts). Two weighting matrices (Q and R) were used arbitrarily, by assuming that Q = I & choosing ($R = \lambda I$), where the suppression factor, λ, serves as a convenient tuning factor for the predictive control scheme. Simulation study had been done to examine various predictive control parameters to explain their effects on the model. An analysis of locations of the closed-loop transfer function poles for model with impulse response revealed the presence of poles outside the unit circle when $\lambda = 0$ and the other design parameters were kept at their nominal values. For large sampling intervals and large values of M and P, instability did not occur but the matrix G^TG was considered to be ill-conditioned since the determinant was near to zero. Hence, the choice of $\lambda > 0$ in this case not only prevented immoderate behavior of the control variable but also to avoid a potential stability problem. A major conclusion is that a significant reduction in the dimensions of the "dynamic matrix" does not significantly degrade control system performance. This work has also shown that in order to implement predictive control, the amount of on-line and off-line computations can be reduced by adopting small dimensions for the matrix. Their controller was applied to a stirred-tank heating system, which had performed better than the traditional PID control.

Maurath, et al. [78] presented a predictive controller design by principal components analysis, which had more rich details and specifications about predictive components and also robustness. In this study, the control horizon was tuned to produce an effective controller tuned using the prediction horizon P as the principal tuning parameter. This method illustrates the calculation of a singular value of the process dynamics to design the MPC. The essential design parameter in their technique is the quantity of principal components of the system, generalized inverse and retained in the approximate inverse process used by the control. The effects of retaining each of the individual components on closed-loop performance and robustness could be easily calculated. Choices of other controller design parameters have a minimal impact on the results of the new method. A particular feature is that explicit move suppression is not required. The controller is based on component selection design through information obtained from a singular value decomposition of the system matrix with diagonal matrix. The controller gain matrix is constructed by selecting the number of components of the pseudo-inverse matrix to be retained. Information on system performance and size of control horizon moves can be easily obtained from the singular value decomposition results and used by the designer to determine how many components are useful. With this information, the designer is able to balance the considerations of system performance and robustness where λ selected is set as 0.1 and 0.01 to estimate its effect on the performance and robustness. Finally, the component selection method was demonstrated in designing and evaluating satisfactory MPC controllers and compared with conventional PI and PID controllers for distillation column models [78, 79].

A pattern-based excitation diagnostic tool (EDT) has been presented by [Hinde and Cooper [80]] . The EDT comprises of prepared vector quantizing neural systems, which have been used to perceive local dynamic behavior to in the recent previous samples of every process variable. The method is based on the on-line diagnosis of process through neural network. The rule base system uses the diagnoses of the NN and estimates when sufficient dynamics is available for regression of a process model. If the outcome model parameters are considered to be corrected, then the proposed model is used to design and update a model based on predictive control. This method is general and is applicable to any number of model-based controllers and fit process model forms. The method has been simulated for chemical process control. For confirmation of the effectiveness, the method has been implemented in real-time for temperature control process. The process consists of two mixing streams of cold and hot liquid. The combined stream then enters a stirred tank. The control objective is to keep the temperature of the liquid in the stirred tank by manipulating the flow rate of the cold liquid using an Electromotive Force (EMF) to pressure transmitter and a pneumatic valve. The liquid temperature in the tank is measured using a type J thermocouple, which is cold junction compensated for using a temperature transducer in the signal amplifier. There is mismatch between FOPDT process and the second order SOPDT model used to produce the training patterns, since this process displays non stationarity, slight nonlinearity and hysteresis. The DMC algorithm is employed using the suppression factor $= \Gamma K^2$, estimated parameter $\Gamma = 10$, and sampling time $T_s = 0.04\tau$. The enhancement of transient response with adaptive DMC compared to conventional DMC and adaptive PI controllers had been approved with noise reduction but still overshoot. The amount of measurement noise was needed to be reduced to get better result. The adaptive DMC made the second set point step response had overshoot similar to the conventional DMC response. However, the tracking result of the adaptive DMC was refined during the third set point step response.

A MPC usually has a group of tuning parameters, such as prediction horizon, control horizon and suppression coefficient. Sometimes, these parameters are modified by trial and error method. This

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trial and error method requires a large amount of simulations based on few tuning rules. This tedious tuning is time consuming for tuning MPC control, due to the complex computations effect of multiple interactive responses between the inputs and outputs on one side and the tuning parameters on the other side. Further, if a process model is ill-conditioned, the tuning task can be very challenging, as the closed-loop system can be easily unstable and the actuators are very likely to become saturated with a typical MPC design. In addition, this traditional tuning usually does not consider the evitable process/model mismatch [81-83]. The prediction horizon should hold comprehensive range of the open loop response sampling data for efficiently creating and ensuring the feasibility to wide range of the signal [84, 85]. Generally, most of the tuning rules for previous studies are not accurate because their MPC parameters do not depend on the process parameters with their sampling time effect and their tuning does not range by controllability rate to cover wide range of industrial processes

Analytical derivation of the move suppression coefficient had been done by Shridhar and Cooper [69] based on assumption that the condition number was around 500 and obtained based on FOPDT approximation of the process, and other MPC design parameters included prediction horizon and control horizon. They also proposed expressions for prediction horizon, and control horizon. Their proposed controller can be applied to DMC in closed loop with SISO stable processes, including wide range of process orders, and non-minimum phase behavior processes. It is a tuning strategy to calculate the control parameters but still needs to estimate the sampling time "(Sampling time Ts/Time constant τ) = 0.05 or 0.15" in the second order and higher order systems; that means needing more steps to design the controller for second and higher order systems, and most models that are easy to apply with FOPDT. Note that the (FOPDT) approximation of the process dynamics is used only for derivation of the tuning parameters of the predictive control. It must be emphasized that the FOPDT approximation should be employed only in the derivation of the analytical expression. The examples presented in this work used the traditional DMC step response matrix of the actual process upon implementation [69].

Research Group from University of South Florida (United States of America) has been working together with Universidad del Norte (Colombia) for few years on a number of projects to investigate predictive control field. One of their best researches done by [86, 87] presented a method to calculate the suppression factor λ using (Analysis of variance-ANOVA), which is a collection of models used to analyze the differences between group means and their associated procedures. Analysis of variance (ANOVA) was performed after collection of values of the suppression factor. ANOVA allows determining the most significant factors for optimal tuning. Only main effects and second order interaction were considered. The analysis was performed to determine the variables that had a significant influence to enhance the suppression factor λ. The experiment consisted modeling a general process as a first order plus dead time (FOPDT), determined using constrained optimization, and the best λ value to minimize a cost function. Industrial mixing process plant has been used to demonstrate the convenience of ANOVA Equation to calculate the suppression factor λ to tune DMC. It is more suitable with first order systems, but inaccurate for higher orders for most systems, because of the limited dead time that calculated to estimate the suppression factor.

A research group from University of New Brunswick presented another tuning strategy of MPC by reconstructing the MPC law with another extended predictive control matrix and strategy shorted as (Ayad). The formulation of the control strategy begins by introducing a weighting move suppression matrix $\mathcal{W}_{\mathrm{Ayad}}$. The structure of $\mathcal{W}_{\mathrm{Ayad}}$ matrix is created to deal with three parameters , $\mathrm{R}_1, \mathrm{R}_2$, and λ, with condition of $\mathrm{M} \geq 3$. The investigation needs the ill-conditioned cases of the formed system matrix by the step response to process model. However, this inversion becomes sensitive to input uncertainties and plant model mismatch. Other simulation studies only included models with small time delay and small ratio in his research. The control strategy uses both the determinant of the system matrix and their condition number (CN) for the control law as parameters for creating method with effective technique for stable processes. The basis of the technique is to moderately bring down the condition number with vast estimations of determinant. The research described the importance of using R_1 to increase the matrix and decrease the condition number of the matrix, especially for the small values of λ. Using the determinant design and calculations, graphs are then plotted to compare and estimate the best value of R_2 by this computational way. It is difficult to calculate the proposed matrix parameters, where $[R_1, M]$ is calculated by empirical estimation. The weights are tuned based on the best range of the condition number CN of $G^T G$ which is normally lower. The strategy applied in some real time applications include speed motor and temperature control system [75, 88, 89].

An article presented in IFAC conference [90] described an adaptive approach for a SISO DMC using neural network (NN) as process model, where the NN is adapted to the suppression and scaling factor from SISO dynamic matrix controller (DMC) through a multi-objective optimization algorithm. To optimize, a nonlinear (NN) process model is used, combined with a multi-objective evolutionary algorithm called Strength Pareto Evolutionary Algorithm (SPEA II) to find better controller parameters for the plant each sample time. Adaptation is an alternative that becomes useful and effective for model predictive controllers. It also shows that for linear or time-invariant processes the value added by adaptation is negligible. Computational load is one of the main problems for this strategy if implemented in a fast real process, but for industrial and chemical process like the one used in their research - pH neutralization reactor- it is not an issue. That means adaption NN method is not suitable for implementation of fast processes. For another kind of processes, the use of multi-objective evolutionary strategy to calculate the control moves should solve the problem. Further research should address the issue of extending the adaptive strategy based on evolutionary learning to multivariate scenario, the inclusion of a better decision making system for Pareto front, and modification to calculate the control moves using the evolutionary strategy as optimizer. In addition, this method takes time for NN learning and optimization. Finally, adaption of NN shows limited enhancement in Cooper's method with long NN optimization time to find better controller parameters, but long time is needed to optimize the parameters.

Different model predictive control synthesis frameworks have been examined for DC–DC quasi-resonant converters (QRC) in order to achieve stability and desired performance [91]. Predictive dynamic matrix algorithm was chosen because of due to its simplicity and efficiency [91, 92]. Multi model MPC (MMPC) was used to provide significant benefits over linear controllers. However, it could not handle severe nonlinear dynamic behavior. The accuracy of the nonlinear approximation can be increased by combining more models. The Nonlinear model inside the control algorithm does not cause major problems from a theoretical point of view [93]. However, from a computational point of view, the optimization problem that should be solved at every sampling time can become so extensive that it makes on-line optimizations almost impossible [94]. Hence, intermediates solutions were introduced to maintain the simplicity of linear input-output model and include a partial or full knowledge of nonlinearity. The extended DMC, in which the control input was determined based on the local linear model approximation of the system, was updated during each sampling interval, by making use of a nonlinear model. The sampling time must be fast enough to cover the process behavior for the operating behavior with fasts dynamics. The prediction horizon must be enough to cover the transient steady state. The extend DMC control scheme for QRC converters was found able to provide better tracking compared to MMPC over the whole range of nonlinear operation with unaffected performance by parameter variations [91].

The tuning strategies for model predictive control are presented in Table 1, shows that most tuning strategies required tune some of their parameters empirically by trial and error, which can be considered time consuming. Bagheri and Khaki-Sedigh [95] and Abu-Ayyad, et al. [75] methods are complicated and more analytical parameters are needed to be calculated. Therefore, a proper tuning strategy is needed to overcome the above mentioned issues with more insight tuning strategy, sufficiently accurate, and also not complicated.

Table 1: Summary of tuning strategies for model predictive control.

Ref.	M	P	λ
[14]	Trial/Error	Trial/Error	Trial/Error
[96]	Trial/Error	M+N	Trial/Error
[79]	Trial/Error	$\left[\frac{t_{80}+t_{90}}{2}\right]/T_s$	Trial/Error
[97]	t_{60}/T_s	$\frac{t_{60}}{T_s}+\frac{t_{90}}{T_s}-1$	Trial/Error
[80]	τ/T_s	$(5\tau+t_d)/T_s$	ΓK^2 Γ : computed by trial and error
[98]	Trial/Error	$t_d+\left(\frac{ST/T_s}{3.5}\right)$	$mP+c$ m & c are tuned parameters
[69]	1-6	$\frac{5\tau}{T_s}+\frac{t_d}{T_s}+1$	$\begin{cases}0 & ;M=1\\ \frac{M.K^2}{500}\left(\frac{3.5\tau}{T_s}+2-\frac{M-1}{2}\right);M>1\end{cases}$
[99]	1	$P=ST$ ST:settling time	$\lambda=3\left(1+\frac{6\,t_d}{P}+\frac{3\,K.t_d}{P}\right)$
[100]	Trial/Error	$P=T_s.N\ \gg 1$ N: long period of open loop long prediction horizon	$T_s/2P$
[87]	1-6	$\frac{5\tau}{T_s}+\frac{t_d}{T_s}+1$	$1.63K^2(\frac{t_d}{\tau})^{0.4094}$
[75]	3-5	$\frac{5\tau}{T_s}+\frac{t_d}{T_s}+1$	$\begin{cases}0 & ;M=1\\ \frac{M.K^2}{500}\left(\frac{3.5\tau}{T_s}+2-\frac{M-1}{2}\right);M>1\end{cases}$
[101]	3-5	$P>\frac{5\tau}{T_s}+K$	$\lambda=0.84K^2(\frac{t_d}{\tau}+0.94)^{0.15}\Gamma^{0.9}$ $\Gamma=0.1, 1, \text{or } 10$
[102]	$1\le M<P$	$10\le P\le 20$	DMC: $0.1\le\lambda\le 10$ PFC: $0.1ST\le\lambda\le ST$
[103]	3	$\frac{t_d+5\tau}{T_s}$	Trial/Error
[95]	1 or 2	Trial/Error	$\lambda=\frac{a-K'_{xd1}}{K'_{xd1}}(X_2+X_1^2)$ $q_p=\frac{Y_2K'_{xd1}-aX_2K'_{yd1}}{X_1(aX_1K'_{yd1}-K'_{xd1})}$

			$0 < K'_{xd1} < a$; $0 < K'_{yd1}$ $X_1 = 1 + a + \cdots + a^{P-1}$ $X_2 = 1 + (1+a)^2 + (1+a+a^2)^2 + \cdots + (1+a+\cdots+a^{P-2})^2$ $Y_2 = 1 + (1+a) + (1+a+a^2) + \cdots + (1+a+\cdots+a^{P-2})$ $a = e^{-\frac{T_s}{\tau}}$
[76, 104-106]	$5 \leq \mathrm{M} \leq 10$	$\left(\frac{5\tau}{T_s} + \frac{t_d}{T_s}+1\right) + 0.2\left(\frac{5\tau}{T_s} + \frac{t_d}{T_s}+1\right)$	$\lambda_{P\gamma} = \left(\frac{K}{10\gamma.T_s}\right) ln(1.01K + \tau^2.\mathrm{Ts})$ where: $\begin{cases} \gamma = 4 \;;\; 0 \leq \frac{t_d}{\tau} < 0.5 \\ \gamma = 3 \;;\; 0.5 \leq \frac{t_d}{\tau} < 1 \\ \gamma = 2 \;;\; 1 \leq \frac{t_d}{\tau} < 1.5 \\ \gamma = 1 \;;\; 1.5 \leq \frac{t_d}{\tau} < \infty \end{cases}$ K: pocess gain, τ:time constant, t_d: time delay, T_s: sampling time, and γ: constant coefficient based on the range of the ratio t_d/τ

Conclusion

This paper provided a wide review for many tuning techniques for different MPC strategies. The tuning techniques give the reader compendium of MPC tuning parameters as listed in Table 1. Furthermore; the review covers MPC industrial applications; Linear and nonlinear MPC Strategies and recent formulations of MPC tuning techniques. MPC for fast dynamic systems are limited and needed to be expansion and discussed. Further, linear MPC technology offers significant capabilities, but still has some difficulties in control of integrating systems and slow rejection of unmeasured disturbances in term of real applications. Through years the tuning techniques represents an easy to use techniques and significant modifications in comparison to conventional predictive control. In addition, the mathematical complexity of conventional MPC tuning parameters gives computational burden that usually lead to problems in practical real time implementation and time consuming. However, researchers have yet to satisfy fully the needs of using ideal MPC tuning techniques in industrial applications. At the same time, academic research continues to develop new techniques that may eventually help industrial applications achieve higher levels of perfect performance.

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