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Model Predictive Control — Status and Challenges

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Abstract: For the last 30 years the theory and technology of model predictive control (MPC) have been developed rapidly. However, facing the increasing requirements on the constrained optimization control arising from the rapid development of economy and society, the current MPC theory and technology is still faced with great challenges. In this paper, the development of MPC theory and industrial applications are briefly reviewed and the limitations of current MPC theory and technology are analyzed. The necessity to strengthen the MPC research with respect to enhancing its effectiveness, scientificness, and usability is pointed out. We briefly summarize recent developments and new trends in the area of MPC theoretical study and applications, and point out that the investigation of MPC for large scale systems, fast dynamic systems, low cost systems and nonlinear systems will be of significance for further development of MPC theory and broadening MPC application fields.

Keywords: Model predictive control, constrained control, large scale systems, nonlinear systems

Since its inception in 1970 s, model predictive control (MPC) has developed from a kind of heuristic control algorithms applied in industry to a new sub-discipline with rich theoretical and practical contents[1−3]. MPC aims at solving constrained control problems with optimization demands. In the last 30 years, MPC was successfully applied to complex industrial processes, showing its great potential of handling complex constrained optimization control problems.

Since entering this century, with the scientific and technological progress and the social development, the requirement on control is getting higher and higher. Rather than traditionally satisfying the stabilizing design, optimization is much more incorporated in control design so as to achieve better control performance. In the meantime, optimization is restricted by more and more factors. Besides traditional physical constraints such as actuator saturation, various constraints brought by technology, safety, economics (quality, energy consumption, etc.) and sociality (environment, urban management, etc.) indices should be incorporated. The contradiction between the higher requirements and the more complicated constraints has become a new challenge for constrained optimization control.

In recent years, many applications are reported in literatures, where MPC was adopted to solve constrained optimization control problems in the areas of advanced manufacturing, energy, environment, aerospace, medicine, etc., such as supply chain management in semiconductor manufacturing[4], autoclave composite processing[5], energy efficiency control in buildings[6], urban waste water treatment[7], flight control[8], satellite attitude control[9], blood glucose control for diabetes patients[10], etc. In contrast with the last century when the industrial process was the main application area, the increasing new application areas of MPC reflect the expectations of the people form this advanced control technology. Based on the analysis of existing mature MPC theory and industrial MPC technology, in this paper, we will point out some existing problems, review the current research trends for these problems, and discuss the possible future research directions of MPC.

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1 Existing problems for MPC theory and its applications

MPC, arisen from industrial process control in 1970s, deals with control problems of constrained systems in the framework of optimization, which implies the study of constrained control developed from feedback stabilization to system optimization. A number of MPC survey papers indicated that the most attractive feature of MPC lies in its ability to explicitly handle constraints[1−3, 11−12]. This ability comes from the model-based prediction for the future behavior of the dynamic system. By putting the constraints on the future input, output or state variables, the constraints can be explicitly incorporated in an online quadratic programming (QP) or nonlinear programming problem. With the popularization of MPC in industrial applications and the maturation of MPC software products, standard QP and sequential QP (SQP) algorithms were widely introduced in solving MPC online optimization problems. Successful applications on thousands of worldwide industrial facilities show that MPC as a practical constrained control algorithm has been widely accepted by the field of industrial process control[1].

Qin et al. in their survey [1] in 2003 comprehensively reviewed the development of industrial MPC technology and its application status. Based on the incomplete statistics for the applications of the products from top 5 MPC software vendors up to 1999, MPC technology has been applied to over more than 4600 devices and processes, covering industrial fields of oil refining, petrochemical, chemical, polymer, pulp and paper, air and gas etc. MPC software product has also been developed over four generations. In China, MPC software development and its typical applications were planned in the national scientific and technological research of the Ninth Five-Year Plan in 1995. Zhejiang University, Tsinghua University, Shanghai Jiao Tong University etc. all developed multivariable MPC software products with independent intellectual property rights, and have successfully applied them to industrial processes. Some companies, e.g. SUPCON, also pushed the commercialization and applications of MPC software products, which strongly pushed the industrial application of MPC in China.

MPC has been successfully applied in industrial processes worldwide. But as an effective technique for solving constrained optimization control problems in current economics and society, it still has some limitations:

1) The existing industrial MPC algorithms are mainly suitable for the slow dynamic processes and the environments configured with high performance computers, which

greatly restricts the generalization of its application to broader fields and cases

In the existing industrial MPC algorithms an optimization problem incorporated with models and constraints should be solved online. 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, also not applicable to the environment configured with low performance computing devices (such as DCS low level control). In [1], Qin et al. categorized the application areas for commercial linear MPC products. Among the 2 942 case statistics, oil refining, petrochemical, chemical industry accounted for the vast majority, specifically 1 985, 550, and144 cases respectively. Although the data are from the statistics in 1999, and only limited to the statistics of the world main commercial MPC software products, the trend reflects MPC scale applications are mainly limited to the field of process industry, especially to the fields of oil refining and petrochemical industries. For a large number of fast dynamic systems in areas such as manufacturing, mechanical and electrical, aerospace etc., without high performance computing devices, such standard optimization algorithms are difficult to meet the requirements of real-time computing with small sampling period. So far it failed in scale applications in these fields.

2) From the application objects, the existing industrial MPC algorithms are mainly limited to linear or quasi-linear processes

The main existing industrial MPC technologies focus on linear systems, and mature commercial software and successful applications are mostly for linear systems. MPC software vendors have also developed some nonlinear MPC (NMPC) products, but, according to [1], the number of NMPC applications was roughly 2 % of the linear MPC applications and far from forming dimensions. Even in the process industry, MPC applications are restricted in the industrial processes of weak nonlinearity, such as refining, petrochemical, etc. For the strongly nonlinear industrial processes, such as gas, pulp, paper making etc., the application of MPC is still rare. There are 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[69]. To fulfill the requirements on MPC in various areas along with the economic and social development, the nonlinearity of control objects or control problems will be more prominent. The importance of developing nonlinear MPC technology is more and more recognized by both control society and industry. For example, two international workshops, NMPC05 and NMPC08, focusing on nonlinear MPC, brought together internationally recognized scholars and industrial experts to critically assess and discuss the current status, future directions and open problems of nonlinear MPC[13−14]. But so far, although the nonlinear MPC has been a very active area in academic research, in industrial practice it is still at the early stage[15].

3) From application skills viewpoint, the existing industrial MPC technologies mainly rely on experience and need ad-hoc design

The majority of existing industrial MPC algorithms use non-parametric models easily obtained in industry, such as step or impulse response model, and achieve optimal control through online solving constrained optimization problems. For constrained systems there is no analytic solution, which essentially brings difficulties for exploring the relationship between the design parameters and the system performance when using conventional quantitative analysis methods. A number of design parameters in these algorithms need to be artificially set and posterior tested by a large number of simulations. Therefore, in addition to the large preliminary costs, the experience of the field technicians also plays a key role in the success of MPC application, and the high level expertise required for implementing and maintaining MPC technology becomes the obstacle to its further application. For over 30 years, the industrial MPC technology and products often contain "relics of the past", and did not get enough support from fruitful results in MPC theoretical research. Recently, the application community has recognized the limitations of the current industrial MPC algorithms which were successfully implemented in process control but basically unchanged in mode. Aspen Technology, as a well-known software company in research and development of MPC technology, is considering to get rid of the traditional mode, and developing new MPC products by absorbing new theoretical results in MPC research[16].

In summary, the application of MPC technology has made great success, especially it has been recognized by the industry process control field as the only advanced control technology which can systematically and intuitively deal with the online optimization control for constrained multivariable systems. But the MPC application areas and objects are still very limited due to the bottlenecks of the existing MPC algorithms. For broader application areas and more complex application objects, one can only investigate and develop applicable MPC technologies based on MPC principles. But systematic methods and techniques are far from clear. In addition, existing industrial MPC algorithms are barely related to the recent rapidly developed MPC theories and did not borrow from the research results to guide the improvement of the algorithms. Therefore, we are facing a series of new challenges when solving various new problems resulting from the current economical and social development.

Compared with the MPC practical applications, the MPC theoretical study lagged behind from the beginning. Throughout the progress of MPC theory, it is not difficult to find that MPC theory has gone through two stages[17]: the MPC quantitative analysis theory from the 1980s to the 1990s, with analyzing the performance of industrial MPC algorithms; and the MPC qualitative synthesis theory since the 1990s, with synthesizing MPC controllers to guarantee system performance. The latter aroused great interest in the academic community because it can deal with linear and nonlinear plants, handle general constraints including input, output and state constraints, and solve control problems with different requests, e.g. stability, optimization performance, robust stability etc. In the past decade, a large number of research papers emerged in the major academic journals, exhibiting profound academic values and methodological innovation, which brought a new highlight to the optimization control of constrained systems.

After more than 10 years of development, MPC qualitative synthesis theory has achieved fruitful results, and has published hundreds of papers with high theoretical values, but the current research results have not been accepted by application fields yet. The reason is that the models adopted in these MPC algorithms are rarely used in industrial field. The research idea starting from synthesis also has some essential shortages.

1) Unclear physical meanings make it difficult to relate with application practice

Different from the MPC quantitative analysis theory, in the MPC qualitative synthesis theory the receding horizon optimization at each step is not facing a known online optimization problem fixed according to practical requests and constraints. The content of online optimization often needs to be synthesized together with the control law. In order to get theoretical guarantee for system performance, in the original optimization problem where the physical meaning is clear, modification of performance indices (e.g. adding terminal penalty term), or supplement for artificial constraints such as terminal state constraints, terminal set constraints etc[18], are often needed. Then the designed control algorithms become more conservative. Furthermore, the artificial constraints and physical constraints together make up the constraint conditions in the optimization problem. So the original constraints with physical meaning will be obliterated in the overall constraint conditions represented by a series of complex mathematical formulas. These conditions need to be checked posterior and are lack of analytical conclusions with physical meanings which are cared by practioners. For example, the feasible solution in practical application means the solution that meets all of the hard constraints on system inputs and states, while in the MPC qualitative synthesis theory, feasibility means satisfying not only these hard constraints, but also a series of additional constraints caused by the control system design, e.g. the constraints of invariant set, decreasing of Lyapunov function, and upper bound of control performance, etc. These additional constraints even become the main part of the constraints, which makes it difficult to be related with practical applications. In addition, for some questions, e.g. how large the feasible region of the constrained system states is; whether the LMIs have solutions; if no solution exists, to what extent the constraints should be relaxed, such that the problem becomes solvable, etc, answers cannot be found in current research results.

2) Heavy online computation burden cannot be accepted by practical applications

The MPC qualitative synthesis theory aims at investigating how to theoretically guarantee the stability, optimality and robustness of the closed-loop control system with the rolling horizon implementation of optimization. Usually, the original optimization problem should be transferred into a new one with new performance indices and a series of LMI constraints. Almost each paper published in this area proposed one or more MPC synthesis algorithms according to the investigated problem. But most of these studies focus on theoretical proof of how to guarantee the system performance with conditions given by the algorithm. As for the algorithm implementation, it is often considered that the optimization problem can be solved by existing software packages, and the cost for online solving the optimization problem is not taken into account. The large number of artificial constraints introduced in the algorithm is necessary for guaranteeing system performance, but it also greatly increases the computation burden of the online optimization. Particularly, for robust MPC problems, since the LMI constraints are related not only to the optimization horizon, but also to the possible scenario of the system uncertainty along time horizon, the number of LMIs will drastically increase and the problem of online computation burden will be more prominent. Although in recent years this issue attracted many attentions, due to the heavy online computation burden, these algorithms are hard to be cared by practitioners, and their successful application cases are rarely reported.

In the early stage of MPC, researchers several times pointed out that the MPC theory lagged behind its application, and there existed a big gap between the two. With more than ten years efforts of the academicians, although fruitful results were achieved in MPC qualitative synthesis theory, its theoretical value was significantly higher than practical value due to the different starting points of theoretical study and application. In fact, the gap between MPC theory and application was not reduced. There is still a long way to go before it becomes an applicable systematic theory for constrained optimization control.

In summary, based on the above analysis, one can conclude that although the industrial application of MPC is very successful, and the theoretical research system of MPC is quite perfect, there is a serious gap between the existing MPC theory and its application, which cannot meet the requirements of the current economic and social development for constrained optimization control. We can summarize the problems of the existing MPC theory and application technology as follows:

1) Effectiveness: No matter for industrial MPC algorithms, or for MPC algorithms designed by the MPC qualitative synthesis theory, the heavy computation burden is the bottleneck for online solving constrained optimization problems, which greatly limits the areas and the cases of MPC application.

2) Scientificness: There still exists a big gap between MPC theoretical research and practical application. Commercial MPC software rarely absorbs new results of MPC theoretical research, and the theoretical research does not pay attention to provide guidance for practical applications. There is still a lack of comprehensive MPC design theory and algorithms both with control performance guarantee and considering computation burden and physical intuition.

3) Usability: The current MPC algorithms are based on the general description and general solving methods of constrained optimization control problems. The costs for maintenance and training as well as the requests on computing environment are high. Low-cost constrained MPC controllers are required, which are simple, applicable to computing environment with lower configuration and easy to understand, just as PID controllers.

4) Nonlinearity: The current main results of MPC theory and algorithms are for linear systems. But in practice, there exist a large number of nonlinear control problems. Research for strongly nonlinear systems, particularly in applications, is still immature.

2 Current research status

With the development of technology, economics and society in this century, the demand for constrained optimization control in various application areas is ever-growing. There is a more clear awareness for the aforementioned inadequacy of industrial MPC algorithms and current MPC theory, which promotes the research of MPC theory and application toward a higher level. Recently MPC has become the hotspot attracting much attention in control field. The number of papers about MPC, published in various academic journals and conferences, stayed high. Just in the past five years from 2007 to 2011, through incomplete search in Elsevier publications and IEEE database, 1 319 papers related to MPC have been found, among which 74 in *Automatica*, 75 in *Control Engineering Prac-*

tice, 164 in *Journal of Process Control*, and 35 in *IEEE Transactions on Automatic Control*. In the IFAC World Congress in 2008 and 2011, the number of papers related to MPC was 131 and 138 respectively. A comprehensive review paper on the industrial MPC technology, "A survey of industrial model predictive control technology"[1], got the CEP Best Paper Award in the 2008 IFAC World Congress, and a comprehensive overview of MPC stability, "Constrained model predictive control: stability and optimality"[2], got the High Impact Award in the 2011 IFAC World Congress. In China, aside from the MPC theoretical research synchronous with the international front research[19−26], the MPC application areas extended from traditional oil refining, petrochemical, and chemical industry, to power system[27], steel[28], ship[29], aerospace[30], electromechanics[31], urban transportation[32], canal[33], agricultural greenhouse[34], etc. New improved MPC algorithms and strategies were also frequently reported.

The recent MPC research status clearly shows that, on one hand, people have high expectation on MPC to solve online constrained optimization control problems, and try to use it to solve more and complex problems in their own fields; on the other hand, due to the inadequacy of industrial MPC algorithms and the limitations of existing MPC theory, they cannot simply use the existing theory or algorithms to solve these problems, and must investigate new ideas and new methods to overcome these limitations. The contradiction between the demand and the current status, constitutes a powerful impetus for the development of MPC theory and algorithms in recent years, and is also the reason why people continue to investigate MPC, even though its theory and algorithms seem very mature. Against the above-mentioned limitations of MPC theory and algorithms, the recent research can be roughly attributed as the following aspects:

1) Study on structures, strategies and algorithms for reducing the computation burden of MPC online optimization

The bottleneck of heavy computation burden for online solving constrained optimization problems in MPC greatly limits its application areas and cases. In order to solve this problem, a wide range of studies on efficient structures, strategies and algorithms have been reported.

a) Structural level: hierarchical and distributed control structure

With the rapid development in manufacturing, energy, environment, transportation, urban construction, etc., more and more attentions were drawn on MPC for large scale systems such as enterprise integrated optimization systems, traffic control systems, drainage systems, waste water treatment system, irrigation systems, etc[7, 35−38]. The characteristics of this type of systems include the complexity in system composition and the model, as well as a huge number of variables. In practice it is almost infeasible to solve the large-scale constrained optimization problems in global way. Thus, aiming at the application requests of practical systems, people always borrow the traditional large-scale system theory to decompose the overall optimization complexity based on the hierarchical control structure. Although the multi-level hierarchical control methods with decomposition and coordination based on the same model have been developed quite mature, taking the model complexity and the real environment into account, a multi-layer hierarchical structure with different models on different layers is more preferable[39]. Study of this multi-layer structure focuses on determining the models and control objectives in different layers, and coordinating the relationships of the different layers. Various effective control frameworks and algorithms are developed thereafter, and the proposed control schemes and algorithms are often verified through simulation or by real data.

In the study of MPC for large scale systems, using distributed structure to reduce the computational complexity gained particular prominence in recent years[40−41]. Distributed MPC decomposes the original large scale constrained optimization problem into several smaller scale ones with the idea of local control based on local information. This approach can not only greatly reduce the computation burden, but also improve the robustness of the system. The research emphasis of distributed MPC includes handling the interconnection couplings of subsystems, optimal decision for subsystems, information exchange mechanism among subsystems, guarantee of global stability, and optimality assessment[42]. In recent years, along with the development of communication technology and distributed control hardware and software, distributed MPC has developed from theoretical research to practical application which covers a number of areas, including process control[43], power systems[44], transportation systems[45], and recently very active multi-agent cooperative control[46] etc.

b) Strategic level: off-line design/online synthesis and input parameterization strategies

In the MPC qualitative synthesis theory, although the system performance can be strictly guaranteed in theory, the additional computation burden caused by the design is always huge, which makes the online computational complexity, the current application bottleneck, more prominent. This is also the main reason why the usability of these new theoretical results is questioned by application fields. To solve this problem, "off-line design and online synthesis" strategy was proposed in the MPC qualitative synthesis theory, which moves part of the online computations to off-line so as to reduce the online computation burden. In [47], a simplified design method is proposed for the constrained robust MPC controller in [18] by using this strategy. In [48], a sequence of invariant sets is off-line designed with respect to nominal system indices, then the control law is determined online according to which optimal invariant set the current state belongs to. Similar design can also be found in [49]. In [50], the optimal control sequences in finite horizon are derived off-line, and the online optimal solution is approximated by the set membership function so as to improve the solving efficiency.

In particular, the explicit MPC controller proposed by Bemporad etc.[51−52] will be mentioned here. Based on the analysis of the online constrained optimization problem in MPC, the controller off-line solves a multi-parametric programming problem, partitions the constrained state space, and designs explicit feedback control law for each region. For online implementation, the controller only needs to choose the corresponding state feedback control law according to the current system state. This method moves a great amount of computation to off-line, and the online computation for the control law is very simple. Meanwhile, it has a solid theoretical basis. Therefore, this method received extensive attentions and further studies on algorithm simplification, extension to nonlinear systems, implementation in microprocessors, etc. were reported[53−54]. However, this algorithm needs to off-line solve an NP-Hard multi-parametric programming problem, and the off-line computation burden will dramatically increase when the scale of the problem increases. At the same time, the exponential growth of the number of partitions leads to huge memory requirements[55]. Therefore, the algorithm can only be applied to small-scale problems. In recent years further researches to solve this problem are reported. In [56], piecewise continuous grid function (Lattice PWA function) was adopted to express explicit MPC solution so as to reduce the requirements for storage space and online computation. Through analyzing the complexity in storage and computation for the QP solving method, [57] proposed an explicit MPC algorithm that is executed partially online, and made a trade-off between the storage space and online computation burden. In [58], explicit MPC algorithm was combined with dynamic programming, and the MPC optimization problem was decomposed into small-scale optimization problems. In [59], approximated explicit MPC algorithm was proposed for nonlinear systems.

The strategy of off-line design/online synthesis can effectively address the bottleneck problem of heavy computation burden in MPC online optimization. But it requires that the original MPC controller design can be decomposed, and a certain degree of freedom for online synthesis should be reserved. Therefore, this strategy is not always available for all MPC qualitative synthesis algorithms.

For industrial MPC algorithms, in order to reduce the online computation burden, heuristic input parameterization strategies[1] were proposed very early, including blocking technology[60] and predictive function control (PFC) algorithm[61]. The former sets the control actions during a time period to be constant, so as to reduce the scale of the online optimization problem at the cost of sacrificing the control freedom, while the latter expresses the control variables as a combination of a set of base functions, and converts the online optimization variables to the coefficients of the base functions with a smaller number. Although these strategies are very practical and have been widely used in real processes, there is still a lack of theoretical guarantee for system stability etc. When applying current stability guaranteed synthesis method to such systems, it cannot work because recursive feasibility is difficult to be guaranteed due to input parameterization. In recent years, further research on this topic has been reported. For blocking technology, [62] adopted time-variant blocking matrices to assure closed-loop stability of the MPC controller. [63] and [64] investigated the feasibility of the move-blocking MPC controller, and proposed some methods to improve the feasibility. [65] proposed a generalized aggregation framework for the MPC optimization variables. This framework can not only cover the above two traditional strategies, but also extend the physical mapping implied in original input parameterization to a mathematical mapping, which provides more design freedom and establishes a necessary foundation for system analysis. On this basis, [66] further designed equivalent/quasi-equivalent aggregation strategies to improve the control performance of the aggregation based MPC algorithms.

c) Algorithmic level: develop improved or approximated optimization algorithms

In recent years, another way to reduce the MPC online computation burden is to make appropriate improvements or approximations for the standard optimization algorithm according to the problem formulation of the online optimization in constrained MPC. In [3], some improvements were summarized for explicit MPC algorithms when solving large-scale QP and nonlinear programming problems. In [55], an extended Newton-Raphson algorithm was adopted instead of the commonly used QP and semi-definite programming (SDP) algorithm, and the computation burden was reduced to less than 10 %. Three fast algorithms were proposed in [67] to online solve QP problems in MPC. In [68], the real-time iteration concept is proposed for solving optimization problems instead of the traditional concept of "optimization until convergence", in which only one iteration is performed at each sampling time period, and the result is connected with the successive optimal control problem through a specific shifting. On this basis, [69] proposed an optimization algorithm based on adjoint derivatives and inexact Jacobian matrix. [70] proposed a fast and large-scale MPC algorithm based on partial tabulation. In addition, there has been a new development on using neural network to solve QP problem. Compared with previous works, the new neural network approach ensures to converge to the global optimal solution, and is with the reduced network structures, thus achieves better results[71].

2) The research on robust MPC theory pays more attention to practical usability

The robust MPC theory was preliminarily formed in the mid 1990 s, and has become the focus of MPC theoretical research since the start of this century. Based on the fruitful theoretical results, recent attention is more close to practice and to solve the related difficult issues.

a) Design of output feedback robust MPC

The early studies on robust MPC are mostly based on the assumption that the system states can be measured, but this assumption does not hold in a large number of real systems. Thus, in recent years, many researches on robust MPC with output feedback were carried out instead of state feedback. Compared with the state feedback design, the reconstructed state error in the output feedback design brought new problems for guaranteeing the system feasibility and stability, which makes the design more difficult. For time-invariant systems with disturbances, [72] designed output feedback MPC controller based on the time-varying state estimator and the tube technique, and its recursive feasibility and stability is theoretically guaranteed. [73] transferred the system with unstructured model uncertainty into a time-invariant system with disturbance in a small feasible region, and designed output feedback MPC controller based on the dual-mode control strategy. For systems with both model uncertainty and external disturbances, [74−75] designed output feedback MPC controllers by adopting fixed state observer and dynamic output feedback method respectively. In [75], the parameters of dynamic output feedback were also taken as the online optimization variables of the MPC controller, which reduced the conservativeness of the design. Similar to [75], [76] investigated the design of output feedback MPC controller for uncertain systems with measurable system parameters.

b) Coordinating the contradiction among feasible region, online computation burden and control performance

In robust MPC, the requests on initial feasible region, online computation burden and control performance often conflict with each other[17]. Therefore, how to effectively balance these three issues becomes the focus of recent research in robust MPC theory. Usually people at first consider how to expand the initial feasible region and to improve the control performance, then explore whether the computational complexity of the online optimization can be reduced through off-line design and online synthesis.

For the online optimization problem of MPC, the traditional way is to take the control variables in the control horizon directly as the optimization variables, and online solve an open-loop optimal control problem. But Mayne et al. indicated in [2] that the controllable region for MPC controller would be expanded and the control performance would be improved, if these control variables were totally or partially formed as system state feedback to constitute a closed-loop MPC controller. The study on closed-loop MPC includes the efficient robust MPC with fixed feedback control law and additional free perturbations[77], and a series of its improvement and development[78−79], and the feedback MPC controller designed based on the periodic invariant set[80]. Recently, [81-82] proposed the concept of multi-step control set and adopted a time-variant multi-step feedback control law instead of a unique feedback law, to increase the degree of design freedom and thereby to reduce the conservativeness. This design method was also applied to LPV systems with bounded parameter variations[83].

In addition, [84] suggested to introduce a relaxation matrix to design MPC controllers for systems with structural uncertainty, so as to broaden the ranges of the systems this design method is applicable to. Taking into account that the constraints in real systems are often linear and nonsymmetrical, thus using a polyhedral invariant set is more realistic and less conservative than the traditional ellipse invariant set, [85−86] proposed a design method for robust MPC based on polyhedral invariant set. The polyhedral invariant set can be obtained by geometric method [87], and can be transformed into solving a set of QP problems. For systems subject to actuator saturation, [88] employed the analytical form of the saturation control law in the constrained control theory, and set different weights for real control law and auxiliary control law, thus improving the controller performance. [89] designed H_∞ MPC controller for model uncertain systems with disturbances, and simultaneously solved the problems of stabilization and disturbance rejection.

3) More attentions on nonlinear and stochastic MPC theory

Nonlinearity and randomness are the common system characteristics in industrial process, and the MPC theory for such systems has some defects, e.g. too many assumptions, difficult in design, conservative conclusions, etc. In recent years, in order to promote the practical application of MPC, the MPC theory for nonlinear systems and stochastic systems has been further developed.

a) MPC design for nonlinear systems

The MPC qualitative synthesis theory developed since the 1990 s has essentially solved the stabilization problem of nonlinear MPC[2]. Moreover, fruitful research results were also obtained in robust MPC synthesis for nonlinear systems[90]. In recent years, aside from stability and robustness, the research on nonlinear MPC further extended to state estimation, output feedback and tracking problems, complex and stochastic systems, as well as explicit and numerical algorithms, etc.[13−14]. In addition, MPC for some specific nonlinear systems was investigated in-depth on the requirement of practical applications.

For nonlinear systems, modeling methods using T-S model to characterize the system dynamics have been developed quite mature. In [91], for nonlinear systems described by the T-S model, according to stability conditions, output feedback MPC controller was designed by using invariant set and LMI, and the feasibility and stability of the MPC controller were theoretically ensured. Similarly adopting the T-S model, [92] designed output tracking MPC controller by combining the off-set free technique, so as to reduce the effect of the disturbance to tracking performance. Similar studies can also be found in [93−94].

Hybrid system is another common type of nonlinear systems, especially suitable to describe non-continuous dynamic systems with logical switches. In 1999, Bemporad et al.[95] transferred a piecewise linear system with logic switching characteristics into a mixed logic system by adding appropriate logical variables, and then designed optimal control and MPC by using mixed programming method. After that, mixed integer programming has become the most commonly used method for solving optimizations for such systems[96−97]. Multi-model MPC is another kind of MPC for hybrid systems, which is in principle similar to the hybrid MPC[98−99]. The biggest difference between the two is that, the MPC for the hybrid logic systems has a more precise characterization for the system, where the switching procedure of the system should be also predicted and optimized, while the multi-model MPC directly adopts some designed rules (e.g. fuzzy rules) instead of optimization to switch among the models in different working points.

b) Stochastic MPC theory

Stochastic system is a class of uncertain systems, but the uncertainty usually meets specific statistical probability. If the probability information is reasonably included into the MPC controller design, we can get less conservative designs. Research in this area can be classified into two categories based on the plant characteristics, i.e., stochastic uncertain models and stochastic perturbation systems.

For stochastic uncertain models with normal distributions, the traditional robust MPC design approach is no longer applicable. [100] proposed the concept of probability invariant set to meet the system constraints with a given probability, and designed MPC controller stable in the sense of expectation. Despite the small technical errors pointed out by [101], the proposed concept of constrained probabilistic satisfaction is different from the traditional robust MPC, which provides a new way of thinking for the soft constraint design of the stochastic systems. Based on this idea, systems with disturbances and with both stochastic model uncertainties and disturbances were further investigated by using tube technology[102−104]. In addition, MPC for Markovian jump stochastic systems also attracted the attention of researchers [105−106]. By appropriate transformation, such research can be attributed to the conventional design of robust MPC controllers.

For MPC design of stochastic perturbation systems, one can learn from the design methods of affine disturbance feedback[107−108]. This method is based on the design idea of parameterization, i.e. to design the control by using previous disturbance information combined with feedback control law and additional control actions. It can be used in both systems with stochastic perturbation and general systems with bounded disturbances. But this method requires the system states to be measurable, so as to calculate the disturbance input by the model. [109] further increased the degree of freedom for this control strategy, and obtained better control performance. [110] made use of the character of stochastic disturbance to design the output feedback MPC controller for systems with unbounded disturbances.

4) MPC applications extended to more fields

Among the recent MPC literatures, a considerable part reported the development of MPC applications. In addition to directly applying the existing technology to industrial processes, it exhibits an expansion of the MPC applications to new levels and to many new fields other than the industrial process.

a) Expansion of MPC applications in industrial processes

In industrial processes, for quite a long time, MPC is mainly used at the dynamic control level to assure the system running on the given operating point, while the task of the optimization level is to set the operating point for each sub-process based on the current working status and the economic indices of production. In recent years, MPC application combined with economic indices is further enhanced. On one hand, economic MPC was investigated which directly puts the economic indices to the dynamic control level[111]. On the other hand, due to the uncertainty and variation of the production environment, real-time optimization (RTO) technology was highlighted which has replaced the traditional steady-state optimization, in which MPC began to play an important role. By combining RTO with MPC and adopting dynamic RTO to substitute previous static optimization, the adaptability to parameter uncertainty etc. can be improved[112]. [113] investigated parallel Dantzig-Wolfe decomposition method and decentralized structure for real-time optimization. In terms of real-time optimization as the technology emphasized by industry, how to take full advantage of the dynamic optimization characteristic of MPC, how to reduce the computational complexity of optimization for large-scale complex systems, and how to effectively adapt to the influence caused by markets, raw materials and other uncertainties, etc., are the important issues for global optimization of industrial processes.

Disturbance is one of the main issues affecting the control system performance in industrial processes. The MPC theoretical research results on tracking control, offset free control, etc., provide effective reference for reducing the effect of disturbance in industrial processes. [114] applied offset free control method to investigate the online computation problem for the operating point in industrial process. [115] adopted offset free strategy to suppress the effect of external disturbances, and applied it to PTA distillation column control, with good results. [116] adopted the robust MPC design theory for perturbed systems in [117] to control practical processes.

In recent years, the industrial applications of MPC also show the concern of industry field for MPC theoretical results and combing them with practice, such as stochastic MPC used in temperature control in industrial oil cooling process[118], explicit stochastic MPC applied to combustion control[119], neural network based MPC algorithms applied to nonlinear industrial systems[120], iterative learning (or repetitive) MPC which embeds iterative learning control (or repetitive control) mechanism in MPC framework for periodically repetitive process or set-point (disturbance) signals[121−123]. These researches greatly promote the combination of MPC theory with applications.

b) Extension to large-scale systems and network systems

Over the last decade, with the rapid development of network technology, on one hand, a large number of hierarchical control and distributed control systems for large-scale plants emerged. In September 2008, EU Seventh Framework Program initiated STREP project "Hierarchical and Distributed Model Predictive Control of Large-Scale Systems", with ten participant groups and lasting for three years. The main goal of the project is to investigate efficient hierarchical and distributed MPC methods and algorithms for this type of large scale complex network systems composed of many subsystems and a large number of embedded sensors and actuators, focusing on resolving the computational complexity, uncertainties and the coordination at each level and among different levels, so as to make the system running safely, efficiently and robustly[124]. The applications of MPC in these systems have been frequently reported, such as hierarchical and decentralized MPC for Barcelona drinking water networks[125]; hierarchical MPC in the municipal waste water treatment systems[7, 126]; hierarchical MPC portfolio control in a power plant[127]; distributed MPC application in accelerated cooling process of metal plates in a steel company[128]; MPC applications in traffic control[129−130], etc. On the other hand, networked MPC closely related to communication procedure has also attracted many attentions. Different from distributed MPC, networked MPC is more focused on the influence of the network transmission on control systems, such as network delay, packet loss, etc. [131] investigated the distributed MPC optimization algorithms in networked environment. [132] made use of the ability of MPC for analytically handling constraints, to design MPC controller based on Lyapunov function for nonlinear systems with transmission packet loss. [133] investigated MPC for systems with constant/time-variant delay and packet loss in forward and backward channels.

c) Extension to new application areas

The energy output provided by new energy systems, such as wind power, solar energy, etc., is always with uncertainty and restricted by many external conditions. The ability of MPC to handle constrained optimization problems makes it favorable in optimizing the operation and maintenance of these systems. For instance, MPC was applied to controlling the oxygen excess ratio of a fuel cell, and achieved good control effects[134]. For solar air-conditioning systems with time delay and non-minimum phase character, sliding mode MPC method was adopted to improve the system robustness and the ability for disturbance rejection[135]. [136] used robust constrained MPC combined with feedback linearization in designing control system for a solar desalination plant. MPC is applied to the wind turbine and wind farm in wind power systems[137−138], etc. In addition, attentions are also attracted to the use of MPC for energy scheduling and management problems[139].

Automotive electronics and ship systems are also the fields where MPC is widely used in recent years. For instance, constrained MPC is applied to ship fin stabilization[140]. MPC with disturbance compensation is applied to guarantee the constraints in ship heading control[141]. Respecting automatic cruise control of automotive vehicles, researches have been carried out on information use, energy saving, and multi-objective optimization problems, and tested in a small car (e.g. SMART)[142−144]. MPC was also applied to automatic car driving/obstacle avoidance and idle speed control problem[145−146] etc.

Traditional MPC is often used in systems with slow dynamics. In recent years, more and more fast systems bring MPC into use to improve constraint handling ability and control performance. In the field of power electronics, [147] proposed MPC method for direct torque control in AC motor to reduce the switching frequency of the electronic components while keeping output torque. Similar studies can also be found in [148]. Since the dimension of such systems is generally low and the storage problem is easy to solve, explicit MPC is often used as the control algorithm for implementation[149−151].

In addition to the above-mentioned fields, MPC application areas also include optimal control of air conditioning systems[152], aircraft control[153−154], robot path dynamic planning[155], even medical[156] and high energy physics[157] etc. The MPC application areas are getting more and more expanded.

5) Studies on implementation of MPC algorithms in underlying control facilities

The implementation of MPC algorithms usually requires high performance computing facilities. With the development of field control facilities and embedded systems, and the expansion of application areas, MPC algorithm also began to penetrate into the underlying level control. How to implement the MPC algorithms on the underlying facilities with limited computing power has become a hot topic in recent years.

The programmable logic controller (PLC) is a commonly used on-site control device. [158] investigated the method of implementing MPC algorithm on PLC. Starting from the idea of explicit MPC and representing the polyhedron by fixed number of vertices instead of surfaces, a fast algorithm is proposed for solving the suboptimal solution of the optimization problem in MPC, and then successfully implemented on PLC.

In current commonly used embedded systems, field programmable gate array (FPGA) attracts researchers attention due to its good computing performance, parallel processing capability and development framework. After carefully analyzing the online calculation procedure of solving the QP problem in MPC, [159] adopted gradient method as the solving algorithm, and implemented MPC in embedded systems by cooperative working of a matrix coprocessor and a master processor with limited capability. For the QP problem in MPC online optimization, [160] compared the advantages and disadvantages of interior point method and active set method when implemented in embedded systems, and pointed out the advantages of the active set method in small-scale problems. Based on dual active set method and with the parallel processing capability of FPGA, [161] designed the QP solving module for constrained systems, and then designed MPC controllers. [162] presented the complete embedded implementation of standard active set method, and applied it to controlling a tracking system, as well as a reverse osmosis membrane seawater desalination system in [163].

The above analysis for the recent development trends of MPC theory and algorithms shows that for the new challenges put forward more and more by technological, economic and social development of nowadays, constrained MPC has become a hotspot in the area of control theory and applications. Researchers are making efforts through various ways and developing constrained MPC theory and algorithms with more pertinence and practicality.

3 Prospect and potential research directions

According to the analysis on the existing problems and the recent development trends of MPC theory and applications, it could be concluded that investigating and developing constrained MPC theory and high-efficiency algorithms has become a major concern. The key issue is to tackle the inadequacy of current industrial MPC algorithms, i.e. heavy online computation burden, high request on implementation facilities and limited application areas, and to bridge the gap between existing MPC theory and practical applications. With this aim in mind, emphasis could be placed on several systems with distinctive academic characteristics such as large scale systems, fast dynamic systems, low cost systems and nonlinear systems. The MPC theory and algorithms should be investigated focusing on the difficulties encountered when applying current MPC technology to these systems, and application tests should be made by typical case studies, so as to improve the real-time quality, scientificness and usability of MPC algorithms, and strengthen the practical pertinence and usability of MPC theory. The relationships of these typical systems with corresponding application areas as well as the existing problems (refer to the summary at the end of Section 1) of current constrained MPC are exhibited in Fig. 1.

1) Large scale systems

For large scale systems where information and control are of distributed features, such as urban traffic networks, drainage networks, large scale production processes, multi-agent cooperative systems etc., the existing object/facility-oriented centralized industrial MPC algorithms cannot be directly utilized due to high dimension and incomplete information. In real-time constrained optimization control the global goal would be accomplished by hierarchical or distributed structures. For different structures, theoretical issues such as convergence of on-line information exchange and iteration in MPC algorithms, global stability and robustness, sub-optimality of performance etc. should be investigated respectively. Aside from that, on the request of MPC application, there are still many difficulties in developing practical and efficient MPC control strategies and algorithms in these large scale systems. For instance:

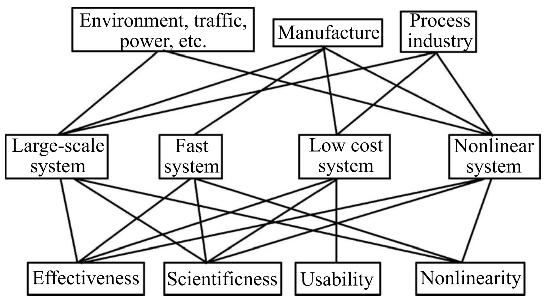

Fig. 1 The relationship between four typical systems and application fields/existing problems

a) The models of urban traffic, drainage and other networked large scale systems are of high complexity (distributed parameter, hybrid, nonlinear, etc). The existing commercial software package with black-box nature can be effectively used for prediction, but not for optimization requiring analytical knowledge. Efficient optimization algorithms based on system simulation should be investigated.

b) In the multi-layer hierarchical control structure of this kind of large scale networked systems, different models should be adopted in different layers. The modeling, prediction and optimization methods in the global, regional and implementation layer should be investigated by using complex network theory, analytical aggregation method and data driven technology respectively. The relationships of the optimization controls between different layers and the corresponding information coordination methods should also be studied.

c) Optimization of large scale production process is facing problems like hybrid mathematical model, products quality testing only available at the end, etc. The MPC application must take systems hybrid characteristic and non real-time feedback into consideration. Besides, for MPC distributed realization, the relationship between global goal and subsystem goals, and the mechanism to improve global performance through coordinating subsystems should be studied.

d) In multi-agent cooperation, the information exchange between agents is strictly restricted and system topology changes with the states. Neither the existing distributed feedback control laws failing to consider optimization nor the distributed constrained MPC algorithms oriented to fixed information structure could be directly adopted. It is necessary to develop effective distributed MPC algorithms for physical constraints, topological constraints and time varying topology. The performance degeneration of the algorithms under constraints should also be evaluated.

2) Fast dynamic systems

Electromechanical systems with fast dynamics are popular in the fields of manufacturing, aeronautics, astronautics etc. Constrained control for such systems is developing from feedback stabilization to optimization control. But the current industrial MPC algorithms, which need repetitive iteration to solve the real-time constrained optimization control problems, has been regarded improper for controlling fast dynamic systems. Therefore, it is necessary to develop high-efficiency MPC algorithms that could preserve constrained optimization characters and is suitable for real-time implementation. Research could be carried out from the following two aspects:

a) In recent MPC research, a series of theories and strategies have been proposed to reduce the MPC on-line computation burden. With that we can strengthen the practicality of algorithms. For instance, to investigate off-line design/online synthesis methods whose computation complexity for online optimization could adapt to real-time request of fast dynamic systems; to advance real-time quality through improvement of optimization algorithms in the generalized aggregation strategy; to solve the conflict between control performance and memory requirement for explicit MPC method, etc.

b) The results of constrained feedback control theory have clear physical meaning, small online computation burden and analytical form in problem description and solving, which is very suitable for fast dynamic systems. However, they are incapable of handling problems with optimization requests. Thus it is necessary to make further extension based on current constrained feedback control theory, including incorporating optimization into current feedback control law design procedure, developing explicit constrained feedback control law capable of simply handling constrained optimization and investigating the performance guarantee theoretically.

3) Low cost MPC systems

Current industrial MPC algorithms are often located at the dynamic control level in the industrial process hierarchical structure. The high price, complicated implementation and debugging procedure, and professional maintenance request obstruct their applications in many simple plants and underlying facilities. With the wide application of distributed control systems, field bus systems and embedded systems in various areas, the research on constrained MPC controllers suitable for underlying constrained optimization control and easy to implement in chips has become urgent. This kind of controllers should not only possess the merits of PID controller concerning cost, debugging, and implementation but also perform better than PID in handling constraints and taking optimization into account, and thus might be accepted by users and become a new universal controller as popular as PID controller. The difficulty for that lies in the restrictions on computation speed and storage space of the underlying control facilities. And further research could be carried out to deal with this problem from the following aspects:

a) From the perspective of algorithm, to investigate the constrained MPC algorithms with simple structure. Particularly when the underlying control is mainly loop control, constraint handling mechanism could be incorporated into the non-constrained MPC controller, such as existing predictive PID controller and internal model controller based on quantitative analysis theory, so as to get the constrained MPC algorithms suitable for low configurated facilities.

b) For MPC online optimization, to further study its simple and fast realization through electric circuits or algorithms on the basis of current research results like realizing QP algorithm with neural networks.

c) Considering different embedded control platforms, tasks could be reasonably organized and distributed through a detailed analysis of the on-line constrained optimization algorithm so as to efficiently realize it by properly utilizing the soft-ware and hardware. It is especially noticeable that computation time depends not only on its specific task but also on the frequency of data communication. How to reasonably balance the two should be considered in designing embedded high-efficiency constrained MPC algorithms.

4) Nonlinear systems

Nonlinear constrained MPC is far from mature both in theory and in application mainly because nonlinear system and its constrained optimization problem cannot be uniformly expressed in parametric form. Today the industry-applied nonlinear MPC algorithms still keep the traditional mode of solving online constrained optimization problem by standard nonlinear programming method. The development of MPC qualitative synthesis theory in recent years has brought many new ideas for nonlinear constrained MPC, yet is still far from practical applications. The key issues of nonlinear constrained MPC include how to handle nonlinearity and reduce online computation burden. Both theoretical study and application could have great development space. According to the requests from current applications, the following aspects should be emphasized:

a) Theoretical study on nonlinear MPC has resulted in lots of algorithms with performance guarantee. However, they still lack in applicability with respect to the acceptance from industry. Thus these algorithms should be further studied in more practical ways. Particularly, the real-time quality should be advanced and the design complexity should be decreased.

b) The applications of nonlinear MPC show that multi-model and multi-parametric programming are two successful methods in practical applications. But they need more theoretical support. At present, many results in linear multi-model MPC theory are obtained from unconstrained cases. Naturally, both algorithm implementation and stability guarantee should be further studied if constraints are incorporated. As to multi-parametric programming method, its off-line computation is already NP-Hard for linear systems. For nonlinear systems, the computation for off-line partition will get much complicated and the explicit control law is only an approximate one. Therefore, how to get the explicit control law with theoretical rigor and realize its off-line design, and how to ensure the control system performance after approximation, should be further studied.

The core of MPC theory and algorithms is on-line constrained optimization resulting from the fundamental characters of MPC. Both for performance guarantee in theoretical study and for real-time implementation of the algorithms, difficulties appear around on-line optimization when incorporating constraints. With current development of economy and society, various areas are raising ever higher requests on solving constrained optimization problem and MPC to emerge as an advanced control algorithm capable of handling constrained optimization is highly expected. Facing these new challenges, more efforts should be made in MPC research to bridge the gap between MPC theory and applications. According to the requests from application areas, high-efficiency algorithms both with theoretical guarantee and meeting the application environment and real-time request should be developed. This study will provide systematical theory and algorithms for various areas to solve constrained optimization problems with solid theoretical basis, strong applicability and considering performances of both optimization and stability, and will also promote the further development of MPC theory. This is the persistent pursuit of MPC research, as well as the future direction for MPC advancement.

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