Universitat Politécnica de Catalunya

Proposal of Thesis

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Automatic Control, Robotics and Computer Vision

TOWARDS THE DESIGN OF FAULT-TOLERANT PREDICTIVE CONTROLLERS FOR LARGE-SCALE SYSTEMS USING SET INVARIANCE THEORY

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Towards the design of fault-tolerant predictive controller for large-scale systems using set invariance theory

Abstract

In this proposal, a research on the design of fault-tolerant predictive controllers for large-scale systems is proposed. Fault detection and isolation are based on set invariance theory and interval observers. The research objective for fault detection is to combine both invariant set-based methods and interval observer-based methods and develop new ideas to detect faults not only in transient state but also in steady state. This point will be the core of this proposed research.

Regarding fault tolerance of large-scale systems, only faults occurring in sensors and actuators are considered. Both fault detection and system reconfiguration are based on multi-sensor and multi-actuator schemes, which can keep stability of systems when several conditions are satisfied even under faults. Other works on multi-sensor and multi-actuator schemes are to improve them with considering model uncertainties and broaden them with interval observers.

In this work, model predictive control is used to implement controllers of multi-sensor and multi-actuator schemes. Besides, model predictive control strategy is also used to design the reference governor which can ensure to meet separation conditions of invariant sets. The final achievements of this work will are attempted to solve problems related to faults of actuators and sensors in the Barcelona Drinking Water Network. However, preliminary results of this proposed methodology takes a probable fault in the pitch system of wind turbine as the case study.

Contents

Acronyms

MPC : model predictive control.
FTC : fault-tolerant control.
FDI : fault detection and isolation.
FDD : fault detection and diagnosis.
LQR : linear quadratic regulator.
AFTCS : active fault-tolerant control system.
PFTCS : passive fault-tolerant control system.
RLQ : reliable linear quadratic
LMI : linear matrix inequality.
AC : adaptive compensation.
QFT : quantitative feedback theory.
VSC : variable structure control.
SMC : sliding mode control.
PIM : pseudo-inverse method.
GS : gain scheduling.
LPV : linear parameter varying.
MF : model following.
AC : adaptive control.
MM : multiple model.
EA : eigenstructure assignment.
FL : feedback linearization.
DI : dynamic inversion.
GIMC : generalized internal model control.
IC : intelligent control.
DMC : dynamic matrix control
EPSAC : extended prediction self-adaptive control
GPC : generalized predictive control
MAC : model algorithmic control
PFC : predictive functional control
QDMC : quadratic dynamic matrix control
SOLO : sequential open loop optimization
LMPC : linear model predictive control
NMPC : nonlinear model predictive control
RMPC : robust model predictive control
CMPC : centralized model predictive control
UPC : Universitat Politécnica de Catalunya

1 Introduction

In modern times, it is very common to see large-scale systems. Generally speaking, a large-scale system is composed of hundreds of constitutive elements and has complex structures such as large-scale communication network and metropolitan drinking water network. All of them place heavy burden on performance monitoring, state evaluation and control strategy. These indicate, as the increase of technical complexity of industrial systems, techniques required to deal with them will also get more and more sophisticated. For most of large-scale systems, they have tight relation with daily life. Their outage may lead to a severe aftermath. For example, familiar systems for ordinary people are drinking water networks and sewer networks. If they break down because of some technical causes, it can be imagined, what a mess our cities and life will be. Most importantly, sometimes these bad consequences can be actually avoided if some technical measurements are taken. Considering these factors, more and more energy has been poured into developing useful and general methodologies for fault-tolerant control of these types of large-scale systems by scientists and engineers. So far, substantial achievements have been achieved and put into practice. But undeniably, it is still a long way.

1.1 Fault-tolerant problems of large-scale systems

Particularly speaking, in this proposal, a control strategy of fault-tolerant predictive control is proposed to control large-scale systems towards an objective of fault-tolerant control(FTC). Generally, in industrial control engineering, a feasible control methodology in controlling of large-scale systems is model predictive control (MPC). Some useful information about MPC can be found in [41] [42] [27]. Particular applications upon this topic can be also found in several references for water networks [9].

In practical cases, large-scale systems consist of some interconnected subsystems. Different subsystems have different dynamics, but sometimes have some similar characteristics. In fact, a common methodology can be considered to control different subsystems of a large-scale system. However, because of existence of much coupling and nonlinearity, especially when considering robustness, stability and communication among different subsystems, centralized control strategies are always use-limited for controlling large-scale systems despite it is widely used in industry. Therefore, in comparison with centralized control strategies, generally decentralized or distributed control strategies play a more important role in many practical applications [44].

Besides, in order to cope with fault tolerant control problems of large-scale systems, acquiring sufficient operational information from large-scale systems and imposing control laws on them are specially crucial. Therefore, there are lots of sensors and actuators used in large-scale systems. Undoubtedly, it increases the complexity of systems and may result in new issues, that is, probable faulty functioning of actuators and sensors. In particular, in some crucial parts, faults of actuators or sensors may lead to fatal impact on security of the whole system. Some catastrophes of aircrafts caused by sensor or actuator outage have occurred in recent decades. They strongly proved this point. Hence, in addition to implement necessary performance required by systems, keeping long-time healthy operation of large-scale systems should also be considered particularly when some faults happen. Especially, developing methodologies to introduce fault tolerant mechanism and MPC to the controller design of large-scale systems will be the main work of future research.

The Barcelona Drinking Water Network will be as the case study of this thesis. This network is a typical example of large-scale system which includes lots of elements such as nodes, pipes, valves, sensors and tanks. Early work done in this network by the Advanced Control

Systems Group (Universitat Politécnica de Catalunya (UPC)) has just considered the MPC (in a centralized and decentralized way) in a non-faulty situation. A further work emphasis will be put on the fault tolerant performance of the whole network, such as sensor degradation and outage, actuator degradation and outage, and pipe leakage and so on. All of potential faults aforementioned need to be dealt with.

1.2 Fault-tolerant control strategies

1.2.1 Invariant set-based FTC

In this work, a FTC approach based on set theory will be the goal of the research. Actuator and sensor fault detection based on sets will be considered. With no doubt, there exist a lot of techniques to detect faults and reconfigure/accomodate systems after faults [21] [56]. However, few of them can not only implement reliable fault detection and efficient reconfiguration, but also simultaneously guarantee the stability of the reconfigured systems.

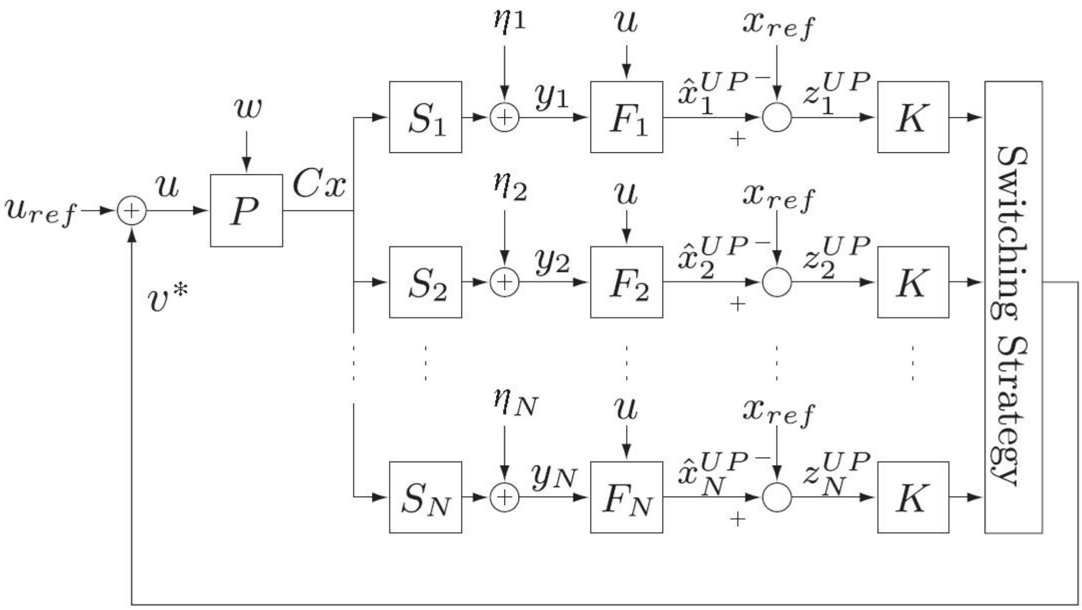

Figure 1: A structure of multi-sensor scheme (taken from [47])

According to [47], a novel multi-sensor scheme for sensor fault detection and system reconfiguration is proposed(See Figure 1). In this scheme, each sensor has an associated state estimator which, together with a state feedback gain, is able to individually stabilize the closed-loop system. At each time instant, the switching strategy selects the sensor-estimator pair that provides the best closed-loop performance, as measured by a control-performance criterion. More importantly, stability of the reconfigured systems are discussed there. If several conditions can be satisfied, the stability of a closed-loop can be guaranteed. The key highlight in this scheme is that the fault detection is based on invariant sets which characterize healthy functioning and faulty functioning of sensors, respectively. The sets are computed off line. If they meet separation conditions, fault detection, isolation and system reconfiguration only are to test whether relevant trajectories of residuals enter into healthy or faulty sets on line. This scheme based on invariant set-testing can efficiently reduce computation burden, improve speed of fault detection and system reconfiguration dramatically, and finally implement robust fault detection. Related to this scheme, [52] [36] have done some improvements for the scheme and make it more feasible.

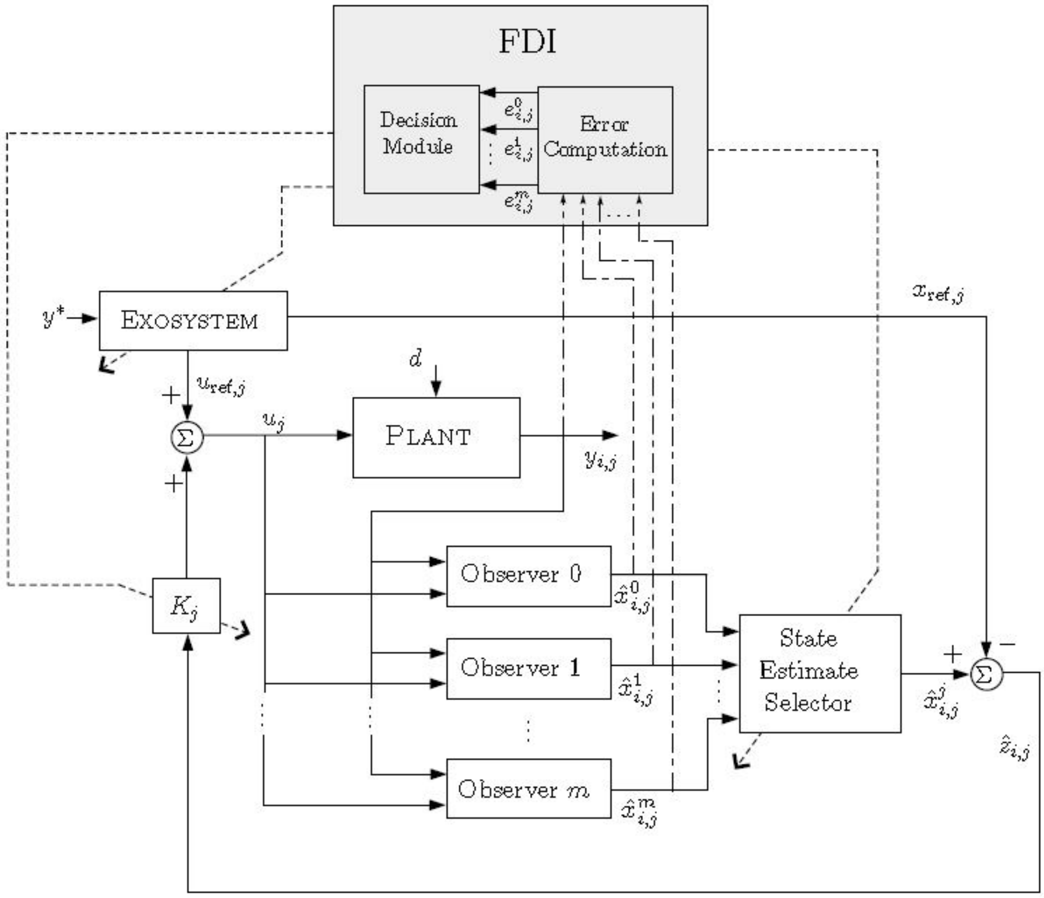

Figure 2: A structure of multi-actuator scheme (taken from [34])

Additionally to set-based fault detection of sensor and reconfiguration schemes, some researchers also have done some research on fault detection, isolation and reconfiguration in case of actuator faults. In [34] (See Figure 2), another novel scheme to dealing with actuator faults is given. It employs a standard configuration consisting of a bank of observers which match the different fault situations that can occur in the plant. Each of these observers has an associated estimation error with a distinctive behavior when an estimator matches the current fault situation of the plant. With this information from each observer, a fault diagnosis and isolation module is able to reconfigure the control loop by selecting a appropriate stabilizing controller from a bank of pre-computed control laws, each of them related to one of the considered fault models. The appealing features for this scheme are that, on one hand, decision criteria of FDI is based on set separation, on the other hand, the stability of closed-loop is also guaranteed explicitly after several conditions are satisfied.

In [48] [46], a similar but improved scheme is discussed. The difference in between is that this author puts her attention on discrete-time system and modifies the separation condition, which is the key of the scheme.

1.2.2 Interval observer-based fault detection

Interval observer-based fault detection method is a robust model-based fault detection method. For this type of methods, the better the model used to present the dynamics of real plant, the better the chance of improving the reliability and performance in detection faults is. In practice, because unknown disturbances and uncertainties of systems are inevitable, residuals are always non-zero even though no faults happen in the system. In order to implement robust fault detection, there are usually two methods to deal with this problem. One is based on decoupling principle, which means the residual is designed to be insensitive to unknown disturbances and uncertainties but sensitive to faults using unknown input observer [11] [14]. But the drawback of this method is that appropriate decoupling is not always possible. The other method, considered as an alternative of this decoupling method, is the interval observer-based approach [40] [15]. In this method, modelling errors are considered as unknown disturbances whose effect on residuals is propagated and bounded.

Interval observer-based method deals with fault detection by employing bounds of unknown disturbances and interval models to consider parametric uncertainties. By propagating effects of unknown disturbances and unknown parametric uncertainties, an interval to bound the trajectory of states of interval observer could be computed. Using the same principle but measurement equation of the system, an interval for outputs of the system can also be predicted. Finally, fault detection result can be determined by means of comparing actual measurements of output with intervals of output predicted by the interval observer at each time instant. Unfortunately, the set of states obtained propagating parametric and noise bounded uncertainty may become extremely complex. In the literature, several approximating sets and related operations have been proposed to enclose and propagate the set of possible states. In [55], a state estimator based on enclosing the set of states by the smallest ellipsoid is proposed. In [15], zonotopes are proposed to approximate state sets of interval observer and provide a way to compute intervals of states conveniently.

In the future work, more energy will be put into the design of a novel fault-tolerant predictive controller on large-scale system, specially based on invariant set theory or combination of the two fault detection methods aforementioned. In this case, the schemes upon set theories above, which are used for sensor and actuator faults, respectively, will continue to be followed, compared and integrated.

2 State of the Art

2.1 Fault-tolerant control

2.1.1 Faults and fault tolerance

As technical systems get more and more complex, they are more and more sensitive to faults. In order to keep the expected performance of the dynamic systems, appropriate measures have to be taken.

In the general sense, according to [5], a fault is something that changes the behavior of a system such that the system deviates from its designed performance. In addition, another more specific understanding of a fault is a deviation of the system structure or the system parameters from the nominal situation. As per the two definitions of faults, it implies a diversity of faults, such as actuator faults, plant faults, sensor faults and so on.

In the presence of faults, to some extent, it always means the performance degradation of systems. In some severe situations, the consequence could be catastrophic to the technical plant, personnel or the environment. Under these circumstances, methods to tolerate faults in the systems need to be explored. For this reason, fault-tolerant control technique combining diagnosis techniques with control methods can be used to deal with faults in an intelligent way. Its aim is to prevent faults which can be handled from developing into failures, hence increase the availability of systems and reduce risks of safety.

2.1.2 Current techniques of FTC

Generally speaking, FTC systems could be classified into two types: passive fault-tolerant control system (PFTCS) and active fault-tolerant control system (AFTCS). The passive FTC techniques are control laws that take into account the fault appearance as a system perturbation. This approach has the advantage of needing neither fault detection and diagnosis (FDD) schemes nor controller reconfiguration, but it has limited fault-tolerant capabilities and a loss of performance with respect to the nominal non-faulty cases.

An illustrative diagram of PFTCS is shown in figure 3, where the diagonal matrix L represents the status of actuator channels. The null value in the i-th diagonal element means that the i-th actuator channel has failed, and the control signal can not get to the system from that particular channel.

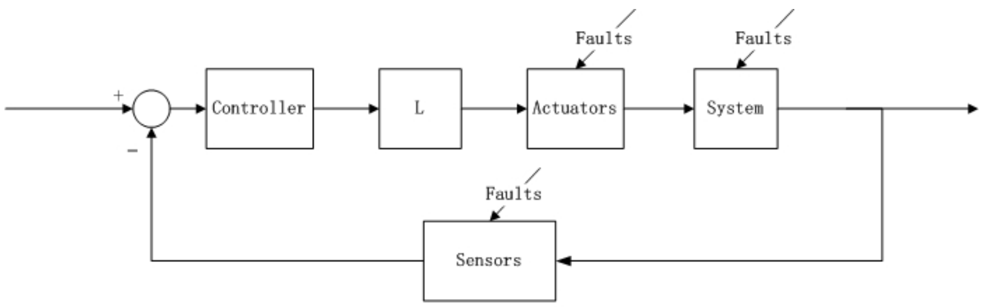

Figure 3: A general structure of PFTCS

So far, some passive FTC approaches found in literature are: reliable linear quadratic (RLQ), H∞ Robust Control, linear matrix inequality (LMI), adaptive compensation (AC), quantitative feedback theory (QFT) and variable structure control (VSC) / sliding mode control (SMC). Early efforts on passive fault-tolerant control were mainly concentrated on using multiple controllers to achieve a reliable control system. A good historical overview about development and research of PFTCS can be found in [21].

On the contrary, active FTC techniques react to the system components actively by reconfiguring control loop so that stability and acceptable performance of the entire system can be maintained. Typically, an AFTCS can be divided into four modules: a reconfigurable controller, a FDD scheme, a controller reconfiguration mechanism and a reference governor. Based on the information from FDD module, the reconfigurable controller can accommodate faulty situations of a system to maintain stability, availability and desired performance. A general structure of a typical AFTCS is shown Figure 4.

- FDD module detects and isolates plant faults as soon as possible, then provides faulty information to other modules.

- Reconfigurable controller maintains stability, desired dynamic performance and steady state performance, based on the faulty information from FDD module.
- Reconfigurable feed-forward controller ensures the closed-loop system to track a command input trajectory in the event of faults.
- Command/reference governor adjusts command input or reference trajectory.
- reconfiguration mechanism organizes the reconfigurable controller in a way such that desired performance can recover as much as possible in spite of faults.

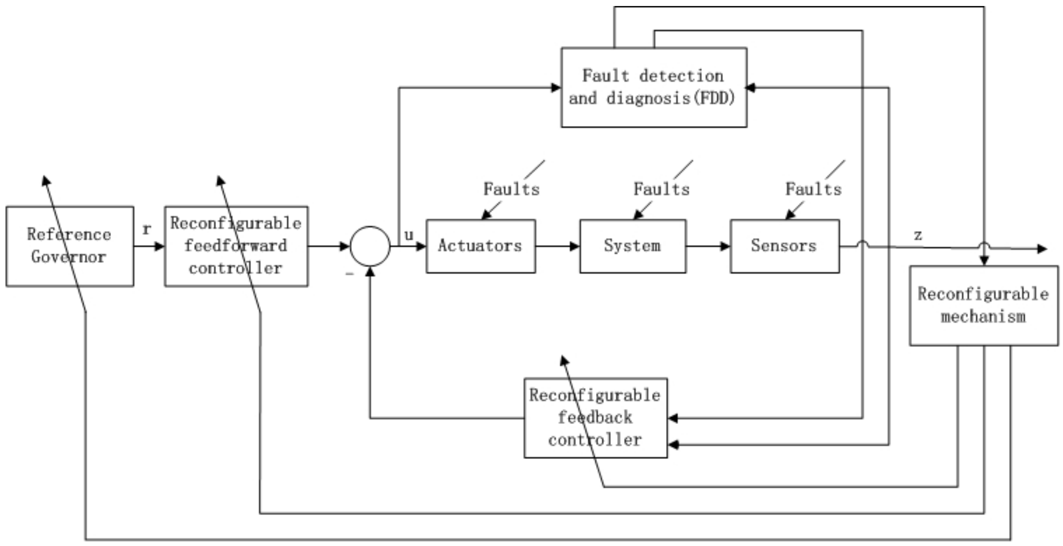

Figure 4: A general structure of AFTCS (taken from [56])

Inclusion of both FDD and reconfigurable controllers within the overall system structure is the main feature distinguishing AFTCS from PFTCS. So far, the existing reconfigurable control design methods fall into one of the following approaches: pseudo-inverse method (PIM), gain scheduling (GS)/linear parameter varying (LPV), model following (MF), adaptive control (AC), multiple model (MM), eigenstructure assignment (EA), feedback linearization (FL)/dynamic inversion (DI), MPC, generalized internal model control (GIMC), intelligent control (IC) using expert systems, neural networks, fuzzy logic and learning methodologies.

2.2 Model predictive control

2.2.1 Principle of MPC

MPC is an advanced control methodology which makes a significant impact on industrial control engineering. It is treated as a powerful approach with proven ability to deal with a lot of industrial problems. In [27], several particular variants of predictive control are listed: dynamic matrix control (DMC), extended prediction self-adaptive control (EPSAC), generalized predictive control (GPC), model algorithmic control (MAC), predictive functional control (PFC), quadratic dynamic matrix control (QDMC), sequential open loop optimization (SOLO) and so on. MPC is viewed as the general name which is widely used to denote the whole predictive control area.

Several subareas in the field are Linear Model Predictive Control (LMPC), Nonlinear Model Predictive Control (NMPC) and Robust Model Predictive Control (RMPC) [31].

MPC includes three essential features: an explicit internal model, the receding horizon idea, and computation of the control signal by optimizing predicted plant behavior. The main characteristic of MPC is to transform a control problem into an optimization problem. The core of MPC consists in the receding horizon idea, which means to compute control signal within a fixed future time horizon at each time instant by optimizing the dynamic behavior of the plant. Then, only the first element of the computed control signal sequence is used as the input of the plant at that step. At next time instant, the same procedure is repeated. There are several main reasons for successful applications of MPC in industry:

- It handles multi-variable problem naturally. In terms of the majority of industrial systems, they are multi-variable dynamic systems.
- It can take account of actuator limitations and cope with input, state and output constraints in a very systematic way.
- It allows operation closer to constraints which frequently leads to more profitable operation.
- Control update rates in predictive control are relatively low, so that there is plenty of time for a necessary on-line computation. Especially, the modern computing hardware is so fast that less and less time is needed to implement the required control low updating.
- Because of the use of the receding horizon principle, it has satisfactory accommodation ability to kinds of disturbances and noise.

For more details, [6] [27] could be referred.

2.2.2 Decentralized and distributed MPC

Most large-scale industrial systems are still controlled by decentralized architectures where the control inputs and control outputs are grouped into disjoint sets. These sets are then coupled to produce non-overlapping pairs for which local regulators are designed to operate in a completely independent fashion. In a typical decentralized MPC framework (see Figure 5) for large-scale systems, at each sample instant, each local controller measures local variables, updates state estimates, solves the local receding-horizon control problem, applies the control signal for the current instant, and exchanges information with other controllers. Nowadays, main application challenges of decentralized MPC for large-scale systems lie in partition of systems and interaction between subsystems. The degree of interaction of the two subsystems affects the stability and performance of decentralized MPC directly. So far, many efforts have been poured into developing methods which can guarantee stability and performance of decentralized MPC in large-scale systems, such as methods based on Lyapunov functions [10], sequential design [16], optimization [12] [45] and overlapping decomposition [18] [19].

In principle, local MPC controllers can be designed with standard MPC algorithm by neglecting their mutual interaction, but very few decentralized MPC algorithms have been developed so far can have guaranteed properties without considering the mutual interaction because of the multi-variable feature of large-scale systems. In [28] [43], a stabilizing decentralized state-feedback regulator for nonlinear discrete-time systems with uncertainties have been derived by resorting to recently developed robust MPC theory and input-to-state stability approach.

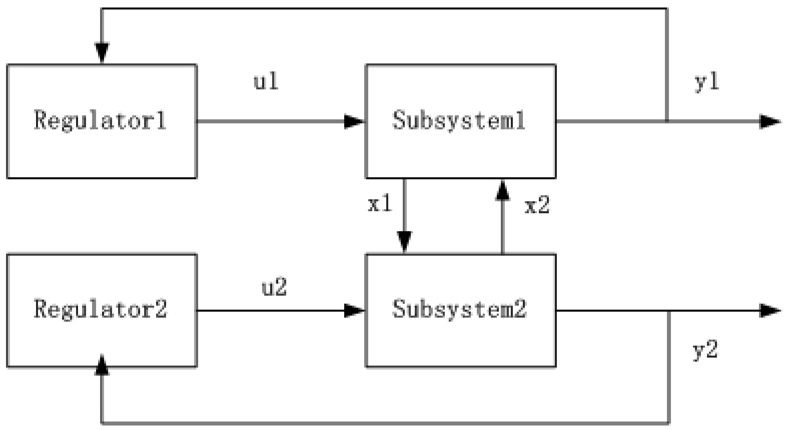

Figure 5: An example of decentralized MPC architecture (taken from [44])

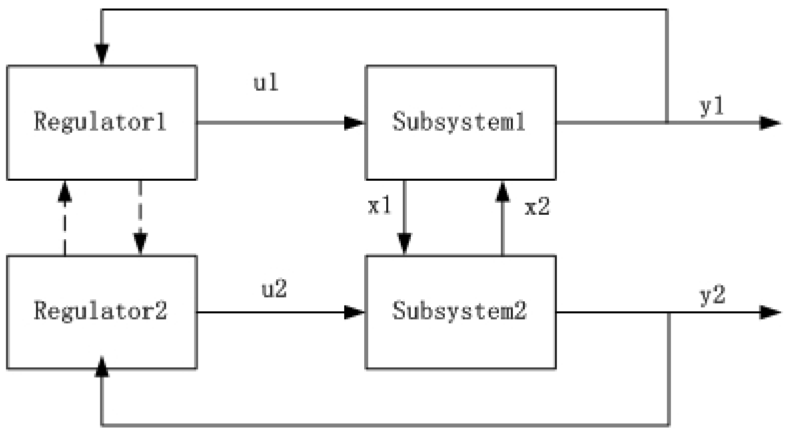

Figure 6: An example of distributed MPC architecture (taken from [44])

By contrast to decentralized MPC, in distributed MPC architecture, it is assumed that some information is transmitted among different local regulators so that each one of local regulators can have some information on the behavior of the others. Figure 6 is an example of distributed control structure. With no doubt, the information exchange among local regulators has a major impact on the performance of the whole system. According to it, distributed algorithm can be classified:

(1) Depending on topology of the communication network.

- Fully connected algorithms: information is transmitted from any local regulator to all the others.
- Partially connected algorithms: information is transmitted from any local regulator to a given set of the others.

(2) Depending on different protocols of information exchange.

- Non-iterative algorithms: information is transmitted by local regulator only once within each sampling time.

- Iterative algorithms: information is transmitted by local regulator many times within each sampling time.

(3) Considering a global performance provided by iterative and non-iterative algorithms.

- Independent algorithms: distributed algorithms where each local regulator minimizes a local performance index.

- Cooperating algorithms: distributed algorithms where each local regulator minimizes a global cost function.

For distributed architectures and algorithms, an alternative to distributed MPC is a hierarchical control structure such as seen in Figure 7. There are two layers in the scheme which depends on a coordinator at the higher layer to coordinate the information exchange between the two local regulators at the lower layer.

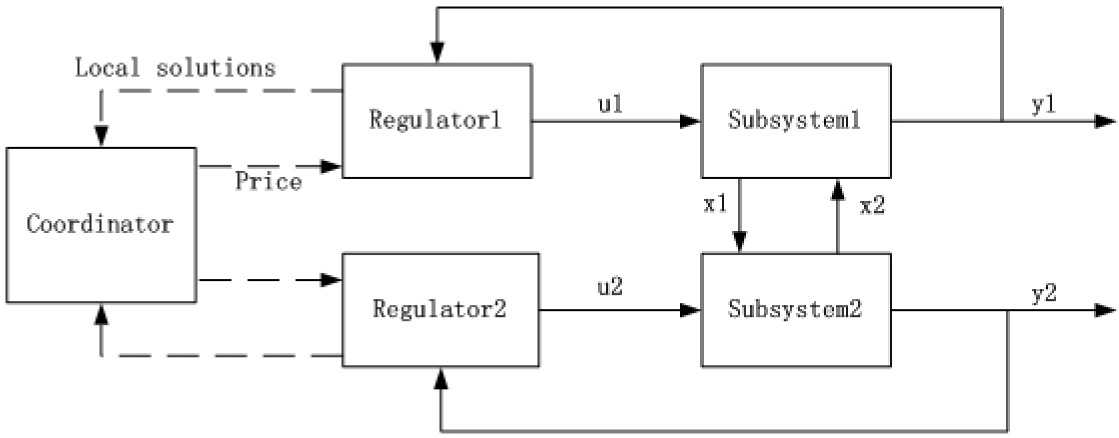

Figure 7: An example of hierarchical control structure (taken from [44])

Below several analysis and applications of schemes aforementioned are listed. In [20], a partially connected, non-iterative and independent MPC algorithm for discrete-time nonlinear systems has been presented. The approach consists of describing the effect of the interconnections among the subsystems as disturbances acting on the local models. Besides, an independent, non-iterative and partially connected MPC algorithm guaranteeing stability for nonlinear continuous-time systems has been presented in [13], where information is transmitted only among adjacent subsystems.

In [7], the system under control is composed by a number of unconstrained linear discrete time subsystems with decoupled input signals. The coupling effect of dynamic system is modelled through a disturbance signal, while the information exchanged between control agents at the end of each steps is the entire prediction of the local state vector. Dynamically decoupled problems are also discussed in [24], the special discrete system is subject to local input and state constraints. The subsystems are coupled by the cost function and by global constraints. System analysis is based on several reasonable assumptions.

Very recently, in [54], it introduces a robust distributed MPC for multiple dynamically decoupled subsystems in which distributed control agents exchange plans to achieve satisfaction of coupling constraints. The local controllers depend on the concept of *tubes* to get robust features and stability. In [3], a decentralized MPC design approach for large-scale systems with possibly dynamical coupling and input constraints is proposed. It supplies a sufficient criterion for analysis of asymptotic stability of the process model in closed loop with subsystem controllers.

2.3 Fault tolerance using MPC in large-scale systems

2.3.1 MPC and large-scale systems

Large-scale systems are characterized by a large number of variables, nonlinearities and uncertainties. Modern dynamical systems, such as nuclear power plants, and many industrial and manufacturing processes, are typical complex systems. According to [8], large-scale systems have a very general meaning and cover lots of different kinds of systems, the author introduces the large-scale systems as three better specified frameworks: distributed systems, discrete event systems, hybrid systems. About applications of MPC in large-scale systems, in the literature, generally speaking, three kinds of MPC are mentioned, which are centralized MPC, decentralized MPC, or distributed MPC.

Centralized MPC is the classical way to implement predictive control. But technological and economical reasons motivate the development of process plants, manufacturing systems and traffic networks with an ever increasing complexity. These large-scale systems are very difficult to control with a centralized structure due to inherent complexity, robustness and reliability problems, communication bandwidth limitations, lack of scalability and maintenance issues of global models in case of controlling large-scale systems [32].

Comparing to centralized MPC, the main thought of decentralized or distributed MPC dealing with large-scale systems is to partition them into several subsystems firstly, then develop separate controllers for each subsystems, finally integrate subsystems to reach a global control objective. In [33], a partitioning method based on graph theory is proposed. After dividing, the original large-size optimization problem is replaced by a number of smaller and easily tractable ones which work iteratively and cooperatively towards achieving a common, system-wide control objective.

Besides, when centralized MPC is applied into a large-scale system, if the dynamics of the large-scale system changes (It is possible in real large-scale systems), inevitably, the whole control law for the whole large-scale system has to be updated, in order to adapt the changes. With no doubt, this means not only a heavy load of computation but also a difficulty to build new models of the large-scale systems on line. On the contrary, instead, decentralized or distributed MPC care more about the relevant changed subsystems whose sizes are much smaller than the whole large-scale system.

2.3.2 Fault tolerance using MPC

As mentioned above, because of the inherent complexity of large-scale systems, they are required to be more fault tolerant so that the system availability is kept high at a maximum possible rate. MPC can handle the control of multi-variable plants, and take account of information on constraints arising from equipment limitations, safety requirements and so on. It usually copes with this by combining linear dynamic models with linear inequalities, which is a powerful combination. In this case, the linear model keeps the dynamics simple, while the inequalities can be used to represent important nonlinearities as well as constraints.

A general idea that MPC philosophy is used to fulfil fault tolerance is just when a fault occurs, the fault detection and isolation (FDI) module passes the fault information to the MPC controller as constraint modifications. Then the constrained MPC controller calculates control inputs and provides them to the plant. Giving MPC controllers enough degrees of freedom (a large enough set of control inputs) enables it to keep the plant close to the required trajectory, assuming that such a trajectory is compatible with the faults.

In fact, this idea of developing fault tolerant control approach based on MPC control has been discussed in the last few years. The author in [26] claims that the inclusion of knowledge of faults in an MPC controller relies on the presence of an efficient and dependable FDI unit, on the capacity of updating automatically the model of the system, and on the control objectives defined for the MPC controller which can be left unchanged after the fault. About the topic combining fault tolerance with MPC, several references are listed below.

According to [37], it is the first to view a simplified version of constrained MPC as a promising tool for reconfiguration. Their scheme was an indirect adaptive approach with the system identification module employing a mixed identification method and the controller being split into two loops (an linear quadratic regulator(LQR) inner loop and an outer linear programme on-line optimization to enforce constraints a step ahead). In [17], the reconfigurable control is approached as a multi-model adaptive control problem in which adaptation occurs by discrete changes to the control algorithm, rather than continuous tracking of a gradually-changing model. In this algorithm, the MPC control strategy is used to control a plant described by a quasi-LPV model which represents a high-fidelity nonlinear model.

In [26], MPC technique as a solution to the reconfiguration problem is investigated. The problem and the proposed solution are outlined and a systematic way of reconfiguring control systems in the event of major failure or damage is found. Besides, Formulations and experimental evaluations of various MPC schemes applied to a realistic full envelope non-linear model of an aircraft is presented in [22]. Moreover, a variety of scenarios of fault and disturbance combinations along with modified and robust formulations of online constrained optimization are investigated.

In [1], MPC based on Dynamic Safety Margin is used in FTC design. The proposed method of FTC is suitable for single and multi-model systems according to the fault type and fault information. In [38], a MPC and FTC scheme is developed using an innovation form of state space model derived purely form data using system identification techniques. In [30], a application of FTC based on fuzzy predictive control is presented. Fault detection is performed by a model-based method using fuzzy modelling. Fault isolation uses a fuzzy decision making method. The model of isolated fault is used in fault accommodation with a model predictive scheme.

In [23], the proposed AFTCS scheme is designed based on integrating the MPC, fault detection filter and logic-based switching approach. Multiple MPCs are designed beforehand by foreseeing the possible faults. One MPC serves as primary MPC. When the fault detection filter detects a fault, primary MPC is terminated and control configuration is switched to one of the backup MPC aimed to different faults, using logic-based switching approach. In [29], a FTC scheme based on MPC to control the concentration and level of a solid crystal dissolution tank is proposed . It uses Dynamic Matrix Control (DMC) which is a variant of MPC by using a step response model to predict the future behavior of the plant so as to manage the faults.

2.4 Application of invariant Sets in FTC

The properties of invariant sets are involved in many different problems in control theory, such as constrained control, robustness analysis, synthesis and optimization. Given a dynamic system, a subset of the state space is said **invariant** if the inclusion of the state at some times implies the inclusion in both the past and the future. Considering the same dynamic system, a subset of the state space is said to be **positively invariant** if it has the property that if it contains the system state at some time, then it will contain it also in the future. In [4], basic definitions and notions about invariant sets are presented.

In the literature, various methods used to implement FDI and FTC mechanisms can be found. However, most of model-based methods are involved in probability theory which is used to analyze specific signals in the system. In contract to these methods, set theoretic methods construct sets to describe faultless and faulty scenarios and could make a final decision if the plant is faulty. Mostly importantly, it could also provide some useful information to stability analysis of the system. The majority of set theoretic methods are based on state estimation through sets by using the models of nominal and faulty behaviors, and consequently inferring a fault of the system. Therefore, the relevant FDI mechanism implemented relies on sets [39].

Several families of sets are used to cope with FTC issues. Different sets could be used to avoid different numerical problems. Ellipsoid approach is conservative but have smallest footprint in the representation. Zonotopes have a potential to balance representation precision and computational requirements, but it is still in exploration. Over-approximating sets could keep a firm complexity but add conservation in computing process.

The main weakness of these sets aforementioned is that shape of sets needs to be recomputed in real time. This may increase the computational complexity dramatically, even conduct to void sets. On the contrary, invariant set has unchangeable shape which is not necessary to be updated at each iteration and could reduce the on-line computational burden. Work for diagnosing faults is only to test the trajectories of signal states and judge if they converge to relative invariant sets, assuming invariant sets of healthy and faulty functioning are separate. Besides, FTC scheme based on invariant sets is also good for system stability analysis. Considering accuracy and computing load, many different methods have been developed to trade off the two points.

Recently, several novel FTC schemes based on invariant set separation are proposed by [47] [34]. The main idea is to describe invariant sets under nominal and faulty situations and with respect to these sets, analyze relative information of states, then construct a control action. Under some assumptions, set separation is used to detect system faults and implement FDI mechanism.

3 Objectives of Thesis

3.1 Splitting of overall objective

The overall objective of this thesis is the design of fault-tolerant predictive controllers for large-scale systems. In order to reach this objective, MPC strategy is chosen to implement the controller. Invariant set-based method and interval observer-based method are used to implement fault detection and isolation. For the sake, this overall objective will be split into several specific objectives below.

- Objective 1 : Compare and combine invariant set-based methods and interval observer-based methods for fault detection.
- Objective 2 : Develop a FTC approach of multi-sensor scheme based on interval observer and compare it with relevant multi-sensor scheme based on invariant set separation.
- Objective 3 : Develop a FTC approach of multi-actuator scheme based on interval observer and compare it with relevant multi-actuator scheme based on invariant set separation.
- Objective 4 : Apply MPC strategy into the FTC of multi-sensor and multi-actuator schemes based on the combination of invariant sets and interval observers.

- Objective 5 : Improve practical feasibility of multi-sensor and multi-actuator FTC schemes with considering model uncertainties.
- Objective 6 : Develop a methodology to put the related research results above into the framework of large-scale systems.

3.2 Formulation of objectives

In fact, objective 1 will be a core in this whole topic because efficient method for fault detection and isolation of system faults will be the first and crucial step for the implementation of the whole objective. Virtually, the basic principle of invariant set-based methods is that characterize healthy functioning and fault functioning of the system with two different invariant sets respectively. If these two sets are separate from each other, it means fault detection can be implemented using this method. The drawback of that is it can only be used to detect the faults in steady state, that is, after the states of the system enter into the healthy or fault sets. As a complement of invariant set-based method, the interval observer method is a method which can be used to detect faults of the system immediately after faults happen. Therefore, this method can be used to detect faults during the transient. In this sense, the combination of these two methods seem to be a good way to implement reliable fault detection.

Objective 2 and 3 are nearly similar. The difference is that they care about fault tolerance of different parts of the system. Objective 2 is related to a multi-sensor scheme in [47] and objective 3 is related to multi-actuator scheme in [34]. The advantages of both schemes lie in closed-loop stability. If a set of conditions (such as boundedness of noise and references) are satisfied, the closed-loop stability can be assured even under faults. This point can improve the applicability of those schemes. But as for multi-sensor and multi-actuator schemes based on invariant sets, the challenge is the satisfaction of set separation of healthy set and faulty set. In reality, set separation involves many factors and hard to hold. Just so, interval observer can be resorted to detect faults and evade the rigid set separation conditions because it only care about changes of the system dynamics and doesn't require rigid separation of relevant invariant sets. In addition, a precondition to use invariant set-based multi-sensor and multi-actuator schemes is that faults need to be known and defined beforehand. In fact, this point is very difficult to be satisfied. It is hard to find out not only the magnitude but also the types of faults. But if turn to interval observers, these limitations of invariant set-based methods are almost not necessary to be taken into account for interval observer-based methods. Actually, both objective 2 and objective 3 consist in utilizing advantages of interval observer, combining the merits of stability and robustness of multi-sensor and multi-actuator schemes and finally improving or broadening the multi-sensor and multi-actuator schemes by this thought.

The work of objective 4 is to implement MPC strategy in multi-sensor and multi-actuator schemes. In multi-sensor and multi-actuator schemes mentioned in [50] [34] [47], linear quadratic regulator (LQR) is employed to implement the control objectives. Particularly speaking, the control objective of the schemes is to make the state of the plant track a reference state supplied by reference governor as much as possible. In fact, if we only consider the tracking performance, LQR is good enough to track the given reference. The related result about the tracking performance of multi-sensor scheme can be referred in [50]. However, this good enough result only consider a few actual conditions. Besides, tracking performance of control system is usually only a basic requirement in real situations. In reality, many other performances should be considered and controlled. Some of them are general control specifications (such as tracking time, steady error and overshoot), but some others even have no relationship with these general control specifications (such as costs of economy and energy). With no doubt, the capacity of LQR is very limitative to deal with these types of performances. Especially when we consider large-scale systems as control objectives in this research, many constraints of them are just like costs of energy and material, economic cost and some other constraints on inputs and outputs. Therefore, MPC is proposed as the control strategy for the multi-sensor and multi-actuator schemes by means of its capacity that can cope with systems with constraints and multi-variables, carry out several control objectives simultaneously and make well use of a priori knowledge related to the system itself and its disturbances. Besides, another important reason why MPC is chosen is because of the reference governor in multi-sensor and multi-actuator schemes based on set separation. It plays a key role to implement separation of healthy and faulty sets. The satisfaction of separation conditions depends on the boundedness of references supplied by the reference governor. By introducing MPC into the design of the reference governor, the reference inputs and states provided by the reference governor can ensure the separation of relevant invariant sets and make the fault detection based on set-testing possible [53].

Objective 5 is to improve the feasibility of multi-sensor and multi-actuator schemes. In [47] [34], the multi-sensor and multi-actuator schemes proposed only assume the plants without model uncertainties. From practical point of view, it is impossible to avoid model uncertainties in reality because of errors originated from modelling methods themselves and errors from linearization of non-linear models. Hence, in order to make the schemes more realistic, model uncertainties have to be considered . So far, two preliminary thoughts about this topic may be followed in the future. The first one is to consider model uncertainties as disturbances, then take the same method just like the proposed multi-sensor and multi-actuator schemes. The advantage of this thought is that it is easy to understand and follow. But the drawback is that this dealing with the schemes results in the conservation of relevant invariant sets. The other thought is to employ linear parameter varying (LPV) form to describe the model with uncertainties, then use the constructions of Rakovic. But this may be more computation-demanding. In the future research, apart from these two thoughts, the energy will continue to be thrown into developing of other efficient ways.

Objective 6 is to connect the work aforementioned with large-scale systems. For large-scale systems, both performance control and fault tolerance are key issues. As mentioned above, because of their complexity, there are many constraints and coupling among subsystems composing large-scale systems. It indicates many challenges will be encountered in the future research. For example, a big challenge before the multi-sensor and multi actuator schemes are put into practice in large-scale systems is how to partition the large-scale systems into small systems as efficient as possible. Another challenge is when using these schemes control subsystems of a large-scale system, because of the uncertain effects from adjacent subsystems, which can be treated as disturbances for considered subsystem , an efficient method have to be developed to deal with this type of real-time disturbances in order to ensure effective working (such as separation of invariant sets) of the schemes.

4 Working Plan

In this section, a research timetable will be presented for this doctoral research. The estimated duration of the doctoral programme is 36 months. During this period, the whole work will be split into several small tasks which are listed below.

- Task 1 : Study of basic bibliographical references about fault-tolerant control, model predic-

	Oct 2011-Sep 2012				Oct 2012-Sep 2013				Oct 2013-Sep 2014			
	Oct-Dec	Jan-Mar	Apr-Jun	Jul-Sep	Oct-Dec	Jan-Mar	Apr-Jun	Jul-Sep	Oct-Dec	Jan-Mar	Apr-Jun	Jul-Sep
Task1												
Task2												
Task3												
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Task8												
Task9												
Task10												
Task11												
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Task14												
Task15												
Task16												
Task17												

Table 1: Timetable of Working

tive control and invariant sets. Understand the basic principles and methodologies related to them.

- Task 2 : Documentary investigating and reading on fault-tolerant control, model predictive control, invariant sets, large-scale systems and the application combining the fields aforementioned, in order to grasp a full view of the relative areas and to know the existing methods for the research topic.
- Task 3 : Collection of materials and study of dynamics and other important features related to large-scale systems.
- Task 4 : Study of partitioning methodologies for large-scale systems, which is important to find and understand detailed problems of controlling large-scale systems, such as interacting and coupling between subsystems.
- Task 5 : Learning of toolboxes used to support the future research in these fields.
- Task 6 : Preparation of the selected case studies to supply a preliminary proof for feasibility of the proposed research scheme.
- Task 7 : Preparation and submission of thesis proposal.
- Task 8 : Deep understanding of the difference between the two different fault detection methods. Find ideas on combination of the two methods.
- Task 9 : Thorough implementation of multi-sensor FTC scheme based on interval observer-based method and its comparison with invariant set-based method. Find several points that can be followed to improve the whole multi-sensor scheme.
- Task 10 : Thorough implementation of multi-actuator FTC scheme based on interval observer-based method and its comparison with invariant set-based method. Find several points that can be followed to improve the whole multi-actuator scheme.
- Task 11 : Designing of a fault-tolerant predictive controller structure for the multi-sensor and multi-actuator schemes aforementioned based on the achievements above, specially considering the actual applicability of the whole integrated scheme from the proposed approach above.
- Task 12 : Exploration of some knowledge to apply the achievements attained yet to large-scale systems.
- Task 13 : Iteration of analysis, improvement and simulation of designed schemes to reach a wide applicability of the research result.
- Task 14 : Cooperation with Supélec (France).
- Task 15 : Publication of relevant achievements.
- Task 16 : Work summarizing and PhD thesis writing.
- Task 17 : PhD thesis defense.

5 Preliminary Results

5.1 Principles of interval observer-based and invariant set-based methods

Disturbances and uncertainties commonly exist in a system. If the disturbances and uncertainties are bounded, it generally means real states are also bounded. Interval observer is just based on bounds of disturbances and intervals of uncertain parameters of models. It is designed according to nominal model of the system and can predict an interval which constrains real states inside the nominal situation. In this case it can predict sets which contain real states at each time instant. When the dynamics of the system changes because of faults, real states may skip out of the intervals provided by the interval observer. Due to this phenomenon, interval observer can be used to detect faults in the system. In [15], a robust fault detection algorithm based interval observer using zonotopes is proposed.

As a comparison, using invariant sets to detect faults implies invariant set separation. Generally, when a fault occurs, the dynamics of the system will change. It means that there are two different models of the same system which correspond to healthy and faulty functioning, respectively. According to invariant set theory, for these two dynamic models, both of them have their own invariant sets restricting states of the system separately. If the two invariant sets describing healthy and faulty functioning of the system are separate from each other, the corresponding fault causing the dynamic change can be detected. In practice, the procedure consists in testing by which invariant set the residual signal is included. If it is contained within healthy invariant set, it means the system is healthy at this time. Likewise, if it is contained within faulty invariant set, it implies the system is faulty.

5.2 Application of interval observer-based and invariant set-based methods

5.2.1 Illustrative example

In [35], a model for three-blade horizonal axis turbine with a full converter and several possible faults of this turbine is proposed. In [51], a method based on invariant set separation is proposed to detect faults in the wind turbine. Here fault 2 which affects $\beta_{2,m2}$ measuring pitch angle β_2 of the second blade is considered. This signal is subject to the following dynamics:

$$x_{\beta_2}^+ = A_{\beta_2} x_{\beta_2} + B_{\beta_2}(\beta_r + \beta_{2f}), \tag{1}$$

$$\beta_2 = C_{\beta_2} x_{\beta_2}. \tag{2}$$

where A_{β_2}, B_{β_2} and C_{β_2} are matrices describing the dynamics; x_{β_2} and $x_{\beta_2}^+$ are current and successor states of the system, respectively; β_r and β_{2f} are reference input and feedback, respectively. The sensor output is given by

$$\beta_{2,m1} = \beta_2 + \eta_{\beta_2,m1}, \tag{3}$$

$$\beta_{2,m2} = [1 + (K-1)]\overline{f}_2 \beta_2 + \eta_{\beta_2,m2}. \tag{4}$$

Above, both $\beta_{2,m1}$ and $\beta_{2,m2}$ measure β_2 and are independent of each other. In this turbine benchmark, fault 2 affects sensor output and f_2 denotes the fault occurrence (1 (0) for healthy (faulty) functioning). $\eta_{\beta_2,m1}$ and $\eta_{\beta_2,m2}$ denote measurement noises of the sensors. K is a scalar indicating the magnitude of fault. The feedback signal is given by

$$\beta_{2f} = \beta_2 - \frac{1}{2}(\beta_{2,m1} + \beta_{2,m2}). \tag{5}$$

5.2.2 Design of interval observer

The interval observer used to predict the states of the system above is designed below as

$$\hat{x}^{+}_{\beta_2} = A_{\beta_2}\hat{x}_{\beta_2} + B_{\beta_2}(\beta_r + \beta_{2f}) + L_{\beta_2}(\beta_{2,m2} - \hat{\beta}_{2,m2}), \tag{6}$$

$$\hat{\beta}_{2,m2} = C_{\beta_2}\hat{x}_{\beta_2} + \eta_{\beta_2,m2}. \tag{7}$$

Where $\hat{x}_{\beta_2}$ denotes observer states; $\hat{\beta}_{2,m2}$ denotes predicted output from the interval observer. Replacing (7) into (6), the final dynamics of interval observer can be written as

$$\hat{x}^{+}_{\beta_2} = (A_{\beta_2} - L_{\beta_2}C_{\beta_2})\hat{x}_{\beta_2} - L_{\beta_2}\eta_{\beta_2,m2} + B_{\beta_2}\beta_r + B_{\beta_2}\beta_{2f} + L_{\beta_2}\beta_{2_m2}. \tag{8}$$

In (8), the initial condition of the system state is given by a zonotope [2]. Observer gain L_{β_2} makes $(A_{\beta_2} - L_{\beta_2}C_{\beta_2})$ stable. Measurement noise $\eta_{\beta_2,m2}$ is bounded according to the model of wind turbine. β_r, β_{2_m2} and β_{2f} can be obtained in real time at each time instant. Because this interval observer is designed according to the nominal model, by (8), the states of the system can be restricted inside zonotopes predicted by the interval observer at each time instant when the system runs operationally.

5.2.3 Invariant set-based fault detection

For (1) and (2), an auxiliary reference system is designed as

$$x^{+}_{\beta_2,ref} = A_{\beta_2}x_{\beta_2,ref} + B_{\beta_2}\beta_r. \tag{9}$$

$x_{\beta_2,ref}$ denotes reference states from the reference system. Besides, a related Luenberger observer for an estimate of the system state is given as

$$\hat{x}^{+}_{\beta_2} = A_{\beta_2}\hat{x}_{\beta_2} + B_{\beta_2}(\beta_r + \beta_{2f}) + L_{\beta_2}(\beta_{2,m2} - C_{\beta_2}\hat{x}_{\beta_2}). \tag{10}$$

Given the expressions of the plant model, the reference system and the observer, the dynamics of estimated state error can be written as

$$\tilde{x}^{+}_{\beta_2} = (A_{\beta_2} - L_{\beta_2}C_{\beta_2})\tilde{x}_{\beta_2} + \frac{1-K}{2}\overline{f}_2(B_{\beta_2} + 2L_{\beta_2})C_{\beta_2}x_{\beta_2} - L_{\beta_2}(1 + (K-1)\overline{f}_2)\eta_{\beta_2,m2}. \tag{11}$$

In this case, a residual for the detection of fault 2 is defined as

$$r^{+}_{f2} = \hat{x}_{\beta_2} - x_{\beta_2,ref}. \tag{12}$$

Replacing (9) and (10) into (12), the dynamics of residual can be deduced. It can be obtained as

$$r^{+}_{f2} = A_{\beta_2}r_{f2} + L_{\beta_2}(C_{\beta_2}\tilde{x}_{\beta_2} + \eta_{\beta_2,m2}) + B_{\beta_2}\beta_{2f} + \frac{1-K}{2}\overline{f}_2B_{\beta_2}(C_{\beta_2}x_{\beta_2} + \eta_{\beta_2,m2}). \tag{13}$$

From (13), techniques of ultimate bounds [49] [25] can be used to compute invariant sets of healthy and faulty functioning in the system. But in reality, only the healthy set of the residual can be computed accurately. The faulty set could not be computed because K is an unknown signal which depends on the faulty situations of the system. Here the main objective is only to compare interval observer-based method and invariant set-based method. Therefore, for details of fault detection of fault 2 using invariant set-based method, please refer [51].

5.3 Comparison and conclusion

In the considered example, the values of relevant parameters in the dynamics are given.

- Matrices of dynamics:

$$A_{\beta_2} = \left[\ 0.8667 \quad -1.2343 \quad ; \quad 0.01 \quad 1\ \right]; \quad B_{\beta_2} = \left[\ 0.01 \quad ; \quad 0\ \right]; \quad C_{\beta_2} = \left[\ 0 \quad 123.4321\ \right].$$

- Bounds of noise:

$$\eta_{\beta_2,m1} = 1.9388; \quad \eta_{\beta_2,m2} = 1.9357.$$

- Observer gain:

$$L_{\beta_2} = \left[\ -0.001 \quad ; \quad 0.003\ \right].$$

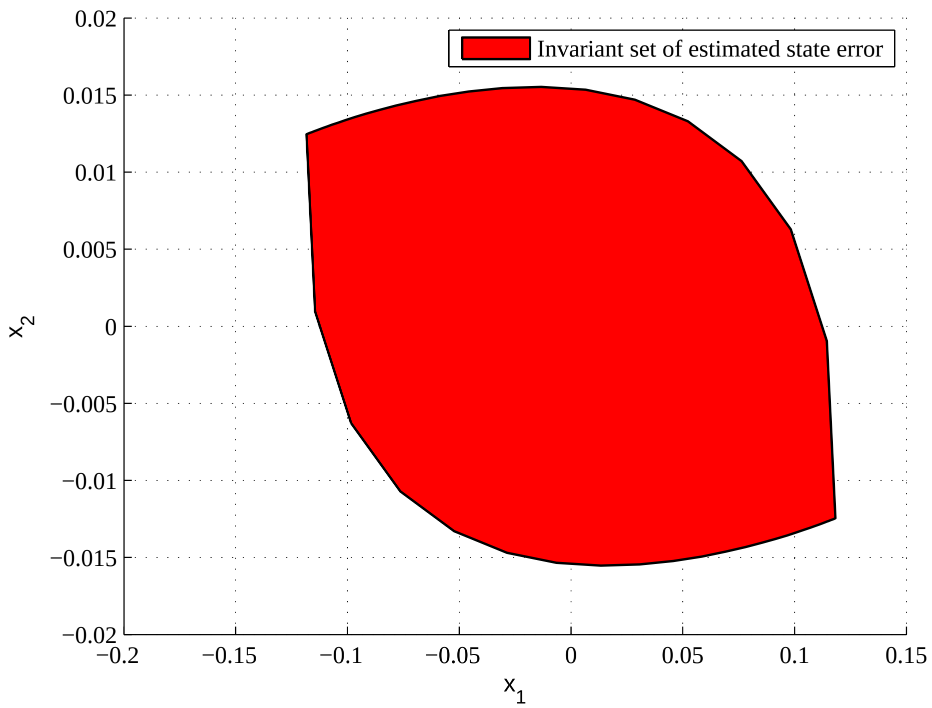

Figure 8: Invariant set of estimated state error

When the wind turbine operates healthily, f_2 is equal to 1. In this sense, relevant invariant sets can be computed definitely. Here it only uses estimated state error $\tilde{x}_{\beta_2}$ to present what may be interested to analyze. In this case, a step signal with an amplification of 3 as a reference input is input. Invariant set of dynamics (11) is showed in Figure 8. In Figures 9 and 10, a comparison of estimated state errors from the two methods is presented. From these figures, it can be stated that:

- The bounds predicted by interval observer converge to those of invariant set of estimated errors.
- The interval observer can predict the whole evolving process, while invariant set-based idea can only present the steady state behavior.

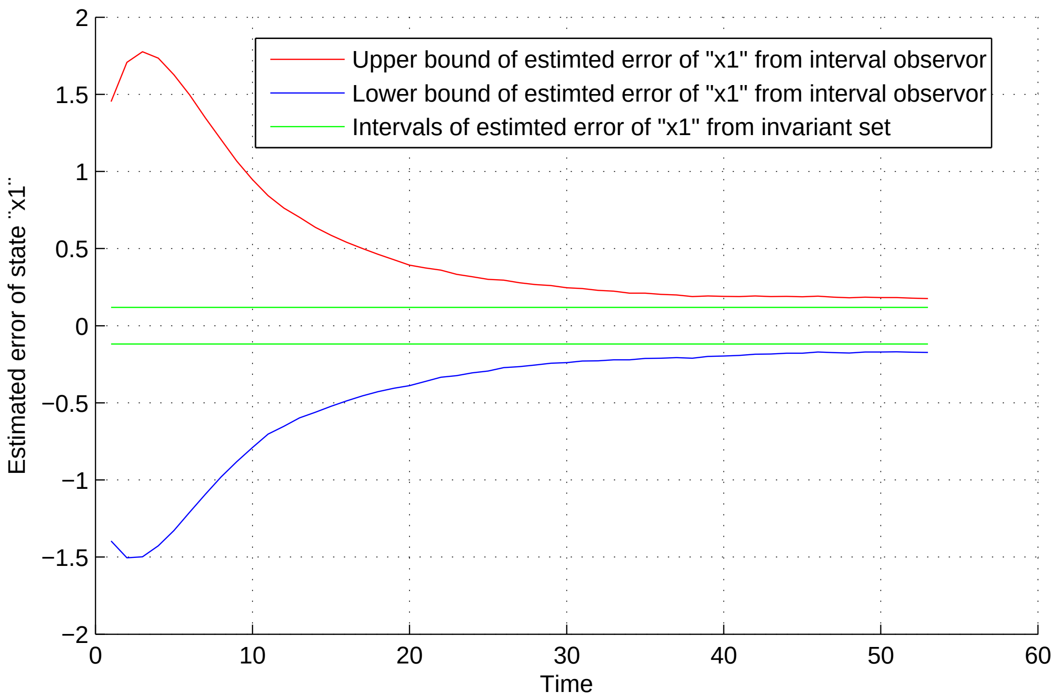

Figure 9: Comparison of interval observer and invariant set (estimated error of state x1)

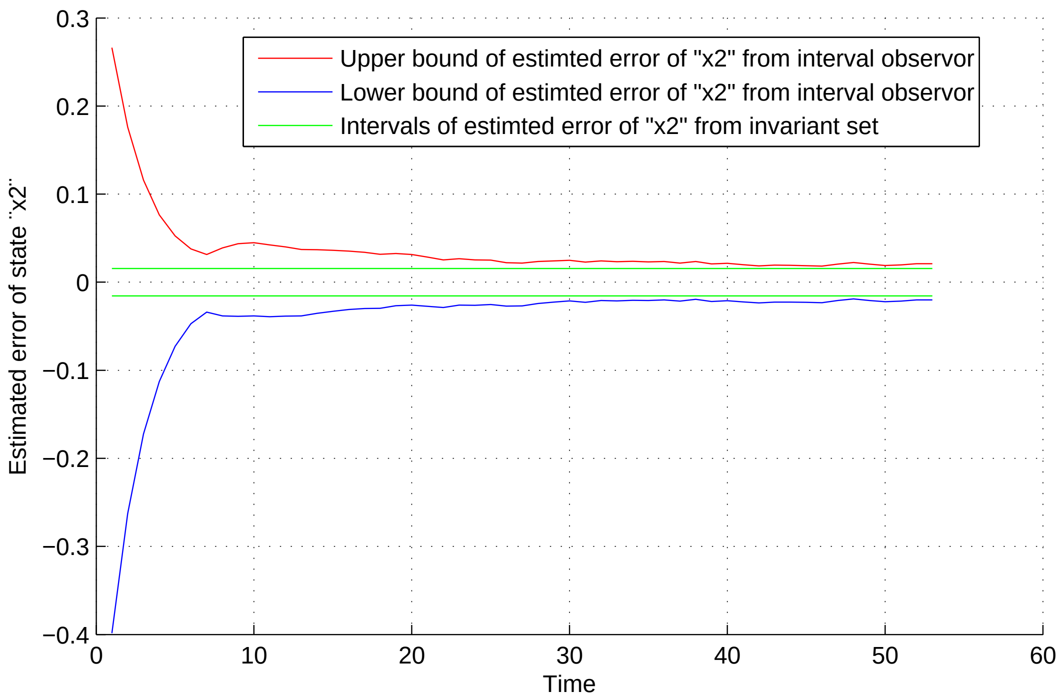

Figure 10: Comparison of interval observer and invariant set (estimated error of state x2)

The two points stated above just reflect the key research goals of the future work. Invariant set-based method can only detect faults after the system is in steady state while the interval observer can predict transitory sets of process dynamics. Therefore, the thought is to compare and integrate the two methods for fault detection. For example, a general idea about this topic is that relevant sets can be obtained at each time instant by interval observers, then test whether residual signal vanishes into these sets at each time instant to detect faults in real time. In fact, only after fault detection, reconfigurable control to tolerate faults can be realistic.

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