COORDINATING MULTIPLE MODEL PREDICTIVE CONTROLLERS FOR LARGE-SCALE SYSTEMS

ABHAY ANAND

NATIONAL UNIVERSITY OF SINGAPORE

2014

COORDINATING MULTIPLE MODEL PREDICTIVE CONTROLLERS FOR LARGE-SCALE SYSTEMS

ABHAY ANAND
B.E. (Hons), Birla Institute of Technology and Science, Pilani, India

A THESIS SUBMITTED

FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

DEPARTMENT OF CHEMICAL & BIOMOLECULAR ENGINEERING

NATIONAL UNIVERSITY OF SINGAPORE

2014

DECLARATION

I hereby declare that this thesis is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis.

This thesis has also not been submitted for any degree in any university previously.

Abhay Anand

Abhay Anand
10 January 2014

ACKNOWLEDGMENTS

I would like to express my sincere thanks to my supervisor, Prof. Lakshminarayanan Samavedham for being such a wonderful mentor. I am greatly indebted to him for his constant guidance, support and encouragement throughout the course of my graduate studies. I have learned a lot from him and his lateral perspectives on education and research have greatly influenced me both academically as well as professionally.

I also owe Prof. Sundaramoorthy a big thank you for getting me started on my research and providing the initial impetus and motivation to pursue this very interesting field of research. I thank Dr. Kiran for being my mentor in the lab, guiding me through the various phases of my PhD. I would also like to thank the Informatics and Process Control Unit (IPCU) team Raghu, Sundar, Kiran, Logu, Prem, Manoj, Vaibhav, Naviyn, Pavan, Krishna, Kalyan and Karthik for helping me shape this work with their valuable suggestions and constructive criticism. It has been a pleasure sharing the lab and working with the IPCU team. A special thanks to Dr. Raghu for introducing me to the Singapore Delft Water Alliance (SDWA).

I would like to thank Prof. Vladan Babovic and Mark Womersley at SDWA, for having great faith in me and funding my research. During my time at SDWA, I have had the privilege to work with some of the most talented researchers. I would like to thank Dr. Abhijit Badwe, Dr. Stefano Galelli and Dr. S K Ooi for their guidance and stimulating discussionSs on various engineering problems. SDWA being an interdisciplinary research organization has helped me understand the need for communication and cooperation in solving real world problems. Working in a diverse environment has been intellectually stimulating and has helped me keep things in perspective. I would like to thank Albert and Ali, my fellow PhD students at SDWA for making my stay at graduate school memorable. I would also like to thank my colleagues at SDWA – Serene, Alam, Pavlo, Petra, Jingjie, Javier, Gerard, Joost and many others for providing an environment conducive to learning. Also a special thanks to Anji, Satya and Jeffro for making life in Singapore all the more enjoyable.

I would like to thank Prof. Rangaiah and Prof. Chiu Min Sen for serving on my qualifying examination committee and providing me with invaluable feedback on my research direction and progress.

I would like to thank the very efficient ChBE and SDWA admin team for helping me process innumerable forms through the course of my studies. Thank you Ivy, Sally, Saedah, Doris and Tan Hui Ting.

Lastly, I would like to thank my parents and my sister Aarti, for their love and constant encouragement.

TABLE OF CONTENTS

SUMMARY

Many large-scale systems are formed by the interconnection of several subsystems, whose different spatial and temporal characteristics make them significantly heterogeneous. The optimal management of such systems must generally deal not only with issues related to large dimensionality, but also with the presence of several interactions between the subsystems, which have a significant influence on the local control decisions and the overall system optimality. For such large-scale systems, model predictive control (MPC) is an attractive control strategy that can be implemented in centralized or decentralized configurations. It has been shown that, to achieve a flexible and reliable control structure with optimum overall system performance, individual decentralized controllers have to be coordinated and driven towards the performance of a centralized controller. In this work, based on three coordination strategies that have been reported in the literature, viz., (1) communication-based coordination, (2) cooperation-based coordination, and (3) price driven coordination, we have reformulated and evaluated different methods for coordinating multiple linear MPCs. These strategies have been evaluated on benchmark chemical engineering systems (via simulations), on the basis of their robustness, stability, and performance in comparison to that of a centralized MPC implementation. The ability to deal with a variety of model uncertainties and varying intensities of interactions are important aspects that have been investigated. Based on the analysis of the different MPC coordination strategies, cooperation-based coordination has been selected as a robust and efficient control strategy and methods to improves its performance have been analyzed.

The number of interactions between subsystems in large-scale systems increases exponentially with the number of subsystems, making coordinated MPC (C-MPC) architecture effective but not computationally efficient. Hence, it is desirable to reduce the computational load of the coordination architecture without significantly compromising the overall performance. In order to achieve this, a genetic algorithm (GA) based optimizer is utilized to identify the trade-off between various optimal interaction topologies and the associated performance deterioration. To enhance the efficiency of the GA optimizer, the relative normalized gain array (RNGA) is used

to identify the most critical interactions and this knowledge is incorporated into the GA optimizer, significantly reducing the search space leading to faster convergence. A common problem involving large-scale control networks is the disruption of communication. Delay or losses in the information exchange could lead to local control decisions that destabilize the overall system. In order to tackle the problem of communication disruptions, the utility of the GA optimizer as a useful and effective tool to handle communication disruptions has also been highlighted. The catalog of pareto optimal solutions generated by the GA optimizer can be utilized as an easy-to-use look up table to identify alternate communication protocols in the presence of disruptions.

Finally, multi-reservoir management has been identified as a large-scale system where the application of coordinated control strategies could have substantial benefits. The application of the C-MPC architecture for real world water management systems is evaluated through the analysis of a two reservoir test case and a high fidelity model of the Alqueva multi-reservoir system in Portugal.

LIST OF TABLES

Table Page

LIST OF FIGURES

Figure Page

ABBREVIATIONS

C-MPC	Coordinated Model Predictive Control
DBRGA	Dynamic Block Relative Gain Array
ERGA	Effective Relative Gain Array
GA	Genetic Algorithm
HIIA	Hankel Interaction Index Array
II	Interaction Index
IM	Interaction Matrix
MIE	Minimum Information Exchange
MIMO	Multi-Input Multi-Output
MPC	Model Predictive Control
MPM	Model-Plant Mismatch
MOO	Multi-Objective Optimization
NSGA	Non-dominated Sorting Genetic Algorithm
PAES	Pareto-Achieved Evolution Strategy
PID	Proportional-Integral-Derivative
PRGA	Performance Relative Gain Array
QP	Quadratic Programming
RGA	Relative Gain Array
RMSE	Root Mean Square Error
RNGA	Relative Normalized Gain Array
RTO	Real-Time Optimization
SISO	Single-Input Single-Output
SPEA	Strength Pareto Evolutionary Algorithm
SSE	Sum of Squared Errors

NOMENCLATURE

Chapter 3

M	Number of Subsystems
$\tilde{y}$	Output variable vector
$\tilde{u}$	Manipulated variable vector
$\tilde{d}$	Measured disturbance vector
$\tilde{G}_p$	Process transfer function matrix
$\tilde{G}_d$	Disturbance transfer function matrix
$\tilde{G}_{ij}(z)$	Transfer function model between the input to i-th subsystem and the output of the j-th subsystem
N_p	Number of step response coefficients for process transfer function
N_d	Number of step response coefficients for disturbance transfer function
P	Prediction horizon
C	Control horizon
N	Model horizon
Y_{iM}	Current measurement of controlled variables
Δu	Change in manipulated variable
$h_i(t)$	Effect of future inputs of other subsystems on the i-th subsystem output
F_{ij}	Effect of past inputs
F_{di}	Effect of measured disturbances
F_i	Cost function
J_i	Cost function of each subsystem
R_S^i	Vector of individual subsystem set point
q_i and r_i	Tunable weights
w_i	Weight on individual objective functions
e_i	Auxiliary variable
v_i	Auxiliary vector
λ	Lagrange multiplier
g^k	Gradient at k^{th} iteration

γ	Valve position

Chapter 4

im_{ij}	Interaction model between the input to i-th subsystem and the output of the j-th subsystem
K_N	Normalized gain matrix
$k_{N,ij}$	Normalized gain of transfer function $\tilde{G}_{ij}$
$\tau_{ar,ij}$	Average residence time of transfer function $\tilde{G}_{ij}$
Φ	Relative normalized gain array

Chapter 5

s_t	Storage $[m^3]$
u_t	Release decision $[m^3/s]$
Δ	Integration time-step
a_t	Inflow from uncontrolled catchment $[m^3/s]$
μ	Mean
C_v	Coefficient of variation
ρ_{flow}	Coefficient of correlation
δ	Standard normal random number
q_t	Total inflow $[m^3/s]$
P_t	Energy production $[kWh/day]$
$\bar{i}$	Water demand $[m^3/s]$
h_t	Reservoir level $[m]$
$\mathbf{x_t}$	State vector
$\mathbf{u_t}$	Control vector
ε_t	Disturbance vector
τ	Time-step
$g_\tau(.)$	Normalized step cost function accounting for the costs associated to the state transitions
$\bar{g}_{t+h}(.)$	Penalty function related to the final state
$\mathbf{x_{t+h}}$	Final state
$\mathbf{u^{max}}$	Upper bound on manipulated variable
h^{sp}	Water level setpoint
h^{down}, h^{up}	Bounds on water levels
Q	flow rate $[m^3/s]$
t	Time$[s]$
x	One-dimensional coordinate $[m]$
q_{lat}	Unit side flow rate $[m^2/s]$

A_f	Wetted section area $[m^2]$
g	Acceleration due to gravity $[m/s^2]$
h	Flow depth $[m]$
C	Chezy coefficient $[m^{0.5}/s]$
R	Hydraulic radius $[m]$
W_f	Surface width $[m]$
τ_{wind}	Shear stress due to wind $[N/m^2]$
ρ_w	Density of water $[kg/m^3]$
w_s	Width of the structure
z_s	Crest level
dg	Gate setting

Chapter 1

INTRODUCTION

1.1 Background and Motivation

A particular class of large-scale systems are characterized by the presence of a network of several interconnected subsystems. The varying dynamics of the individual subsystems and the presence of several interactions between these subsystems make these large-scale systems significantly heterogeneous with local control decisions having a significant effect on the overall system optimality. Thus, the optimal management of such systems is a challenging endeavor. Real-time management in the form of Model Predictive Control (MPC) is one of the most popular techniques implemented for such systems due to its ability to use real-time data and forecasts to predict future outcomes. MPC has now evolved into a successful control strategy for the integrated control of large-scale multi-variable processes that are subject to operational constraints. Two common paradigms for the implementation of MPC are the centralized and decentralized control implementation. In a centralized MPC implementation, a single monolithic controller is designed and such an implementation is plant-wide optimum. However the centralized implementation is computationally intensive, relatively difficult to implement, tune and maintain, and is characterized by poor fault tolerance (Venkat et al. (2007)). On the other hand, a decentralized MPC implementation involves the design of multiple independent controllers to manage individual subsystems. While such a strategy is flexible, reliable and easy to implement and maintain, it leads to performance deviations from plant-wide optimum. Centralized and decentralized controllers define the limiting extremes of plant-wide multivariable constrained controller design. The performance deterioration of decentralized control as compared to centralized control is due to the controllers ignoring or inadequately modeling subsystem interactions.

The failure of the North East American power system in August 2003 is an apt example of a large-scale system where a centralized controller was not a practically viable option (due to the size of the system) and the implementation of a completely decentralized control scheme resulted in disaster when one of the subsystems (power plants) failed and the failure systematically cascaded across the neighboring subsystems causing a blackout across 8 states in 2 countries. A total of 256 power stations failed in less than 7 minutes affecting 55 million people. Estimates of the cost of damages due to this blackout were between 4 billion and 10 billion USD [1]. Such examples motivate the need to improve the management of large-scale systems, through the development of better control structures.

An alternative to these traditional control paradigms would be to develop a control algorithm that works towards combining the advantages of both the centralized and decentralized control strategies while addressing their drawbacks i.e., the decentralized structure of the system is maintained but the performance is driven towards that of a centralized scheme. This calls for the design of coordinators to provide

[1] https://reports.energy.gov/BlackoutFinal-Web.pdf

a dynamic performance equal to that of a centralized control scheme while maintaining the existing decentralized structure and current research is oriented towards designing robust and computationally feasible controller coordinators.

The coordinator facilitates the communication of information such as states, predicted output trajectory information and calculated control action at each time step between the individual model predictive controllers. This communicated information along with the interaction models and a modified objective function enable every individual model predictive controller to calculate an improved set of control actions directed towards plant-wide optimality. However, most of the research on coordinated model predictive control has been derived based on the assumption that all subsystem interactions are equally important. A coordinator designed in such a manner is computationally intensive and can coordinate the individual MPCs only when information from every one of the subsystems is available. Coordinators that prioritize the various interactions and coordinate the individual MPCs based on the relative significance of interactions would be able to lead to near plant-wide optimal performance with significantly lower computational burden. Current literature is sparse in methods to design coordinated model predictive control algorithms with minimum information exchange between the local controllers such that the degree of decentralization is maximized while at the same time the performance degradation is minimized. In this sense, the controller topology (interaction structure) is first optimized and the local controllers are then selectively coordinated. Also, in model predictive control of processes, the quality and fidelity of the model is imperative for the performance of the controller. The accuracy and validity of the models will change over time and result in a deteriorated controller performance. This necessitates the challenging task of designing coordinated model predictive controllers that are robust to parameter variations, disturbances, mismatches in the models and inaccuracies in the forecasts.

The advantages of coordinated MPC algorithms are not limited to process engineering problems, but would also greatly benefit other systems such as multi-reservoir management systems. These systems of interconnected reservoirs are used not only for supplying drinking water but also for a wide variety of purposes including hydro-power generation, controlling floods and lifestyle attractions. The utilization of reservoirs for a variety of purposes provides the reservoir operators with multiple and often conflicting water quantity and quality objectives. The large dimensionality of these systems, as well as the strong nonlinearities in the various subsystems, can prevent the utilization of integrated and centralized control strategies. Also, the presence of different regulation authorities, each one governing one or a few subsystems, can provide a strong resistance towards adopting centralized controllers, even when these methods are technically viable and hence results in the adoption of decentralized control strategies, which neglect the interactions between the subsystems, leading to suboptimal performances that often result in economic as well as social losses such displacement of populations. The drawbacks of both the centralized and decentralized control paradigms provides a window of opportunity for developing and implementing a physically and computationally feasible coordinated model predictive control strategies for multi-reservoir management.

Centralized controllers are plagued with computational and organizational hurdles and to our knowledge there are no centralized control systems in operation for the management of large-scale industrial systems. Most large-scale systems are managed through a network of independent decentralized controllers. This work explores the potential of utilizing existing decentralized architecture and improving the overall system performance without performing a complete control system redesign. Despite not being implemented in real world systems, the centralized control architecture is used as a theoretical benchmark (performance wise) to compare and assess the performance of a minimum information exchange based coordinated model predictive control architecture that we have developed. The outcome of this research is a novel methodology that combines interaction analysis and coordinated control strategies for an improved optimal management of large-scale systems.

1.2 Objectives

The overall objective of this research is to develop a novel coordinated model predictive control strategy that can be implemented in real-time for the control of large-scale systems. Of particular interest is the multi-objective multi-reservoir management problem. To achieve our objective, the work has been sub-divided into a number of specific objectives:

1. To analyze the existing state-of-the-art techniques in coordinated model predictive control critically. A comprehensive review and evaluation of the existing techniques will help identify opportunities for improvement and provide a base for developing a new strategy.

2. Develop a novel coordinated model predictive control strategy that can be implemented in real-time for the control of large-scale systems. The existing coordination techniques are computationally intensive and there are very few studies on the robustness of these algorithms and their performance in the presence of model-plant mismatch and uncertainties in forecasts has not been studied before. The algorithm that is developed in this work will be designed to address these shortcomings.

3. Develop a methodology to lower the computational requirements of coordinated model predictive control strategy without compromising the overall performance of the system. This can be achieved by reducing the communication demands in the developed coordinated MPC scheme.

4. Identify an interaction measure that can be used to prioritize the interactions between subsystems in a large-scale systems and utilize the interaction quantifier to reduce the communication load on the coordinator, making it faster and more reliable.

5. Implement the developed novel coordinated control strategies on a large-scale, realistic simulated system.

1.3 Thesis Organization

In the second chapter, the current state-of-the-art real-time control strategies used for the optimal management of large-scale systems has been reviewed. Recent advances in the area of coordinated control and their applications has been presented and discussed in this chapter. In the third chapter, three popular coordination techniques viz. communication based, cooperation based and price driven coordination are described in detail and their drawbacks and advantages are discussed. The development of the coordination strategies forms the methodological framework that is employed for all subsequent analyses. A comparison of the different coordinated MPC techniques on popular chemical engineering benchmark problems has also been provided in the third chapter. The third chapter also analyses the effect of model-plant mismatch on the performance of the coordinator and the merits and limitations of the various strategies and their field of application has been discussed. In the fourth chapter, a novel minimum information exchange based coordinated MPC framework is presented. The formulation of the minimum information exchange problem is defined using the MPC coordination technique selected from the analyses in the previous chapter. The model-based interaction analyses and the mathematical formulation of the optimal controller topology with minimum information exchange are described in detail. Also, the utility of the interaction topology optimization to deal with communication disruptions was described in this chapter. The key conclusions and empirical evaluations derived from this work are summarized in the last section of the fourth chapter. In the fifth chapter, the coordination algorithms were implemented on two cases studies to highlight the utility of coordinated model predictive controllers for multi-reservoir management. In the first case study, a two-reservoir network with disturbance uncertainties was considered. In the second case study, the coordinated MPC strategy was implemented on a high fidelity model of the Alqueva multi-reservoir system in Portugal, a large network consisting of a number of interconnected reservoirs with multiple management objectives. A comparison of the performance of the coordination-based algorithm with the traditional centralized and decentralized strategies is provided and the scope to improve the existing operations of real world systems is brought forth. In the final chapter, the key conclusions of this dissertation are summarized along with recommendations for future research work.

Chapter 2

LITERATURE REVIEW

2.1 Control Architectures for Large-scale Systems

Many large-scale systems that are formed by a network of interconnected subsystems has been investigated in this thesis. The varied spatial and temporal characteristics of the individual subsystems make them significantly heterogeneous. Such large-scale systems could be spread across cities and the timescale of individual processes could vary from a few seconds to a few weeks. Moreover, the dynamics of the individual subsystems as well the interconnections between subsystems could by highly nonlinear making them hard to model and control. Also, the presupposition of centrality fails to hold for such systems due to the lack of centralized computational capabilities and/or centralized information management (Sandell et al. (1978)). A few typical large-scale systems that can be described by these attributes are chemical process plants, flood and water management systems, traffic flow control in road and railway networks, power generation and distribution networks, etc.

The escalating importance of the economic efficiency of systems has necessitated the design of large-scale systems with ever increasing complexity. The control systems for such large-scale systems are often designed with a hierarchical structure (Scattolini (2009)) and usually, a multi-tiered hierarchy is considered (Lygeros

(1996) and Fucai et al. (2001)). At the lowest regulatory layer, PID-type controllers are employed to regulate the individual process variables (control loops). In the next layer, local model predictive controllers (MPC) are designed using detailed models (which could be nonlinear) of different sub-systems (units). A short time horizon is considered to predict and control the operating conditions of the system (Pappas et al. (2000)). This layer is succeeded by an MPC Coordinator where, information in the form of states, predicted input and output trajectories, etc. are transmitted between the various subsystems (Stewart et al. (2010)). The coordinator ensures that the goals of the higher level are attained and also manages information flow within the immediate lower layer (a layer containing local MPCs). At the top of the hierarchy, optimal plant performance is coupled with economic objectives and Real Time Optimization (RTO) is performed over a long time horizon (Zanin et al. (2002)). A simple and abstract model of the system is used in this layer of the hierarchy to obtain targets for the lower levels. Since a simplified and steady state model of the process is being used at this level, the model needs to be periodically updated. At the topmost layer scheduling of the various processes within the system and plant wide decision making is carried out over a long planning horizon generally in the order of weeks or months. This hierarchy is depicted in Fig. 2.1. Studies in the literature (Scattolini (2009)) have shown that there needs to be a certain level of integrity between the models used at the different levels of the control hierarchy. In the third level of the hierarchy, the coordinator works toward integrating the local model predictive controllers at the lower level. The coordinator incorporates the goals derived by the layers above in its objective function and uses the information from the individual model predictive controllers at the lower level to drive the plant performance towards the overall optima. Information such as states, predicted trajectory information and calculated control action at each time step are relayed between the local model predictive controllers to decide the best set of control actions.

There has already been a lot of research on the design of multi-tiered hierarchies for the control of large-scale systems (Tatjewski (2008) and references therein). Methodologies for the design of the lower level regulatory controllers and the layer of supervisory MPC controllers as well as the integration of decisions between these layers has also been well documented (De Souza et al. (2010)). Current research is oriented towards designing the MPC coordination layer and the RTO layer and developing a robust methodology to integrate the decisions of these layers to improve the overall system-wide performance (Yip & Marlin (2004)). While most layers of the hierarchy have been well researched, the MPC coordination layer is a new addition to the traditional hierarchical structure and algorithms to coordinate the lower level MPCs have not been conclusively established.

2.2 Model Predictive Control and its Application

MPC is one of the most attractive real-time control strategies (Allgower & Zheng (2000), Qin & Badgwell (2003)) for control of large-scale integrated systems. MPC, which originated in the 1970s, has evolved and developed into a successful strategy to control multivariable processes that are subject to operational constraints (Camacho & Bordons (2003)). MPC controllers work by utilizing a process model to

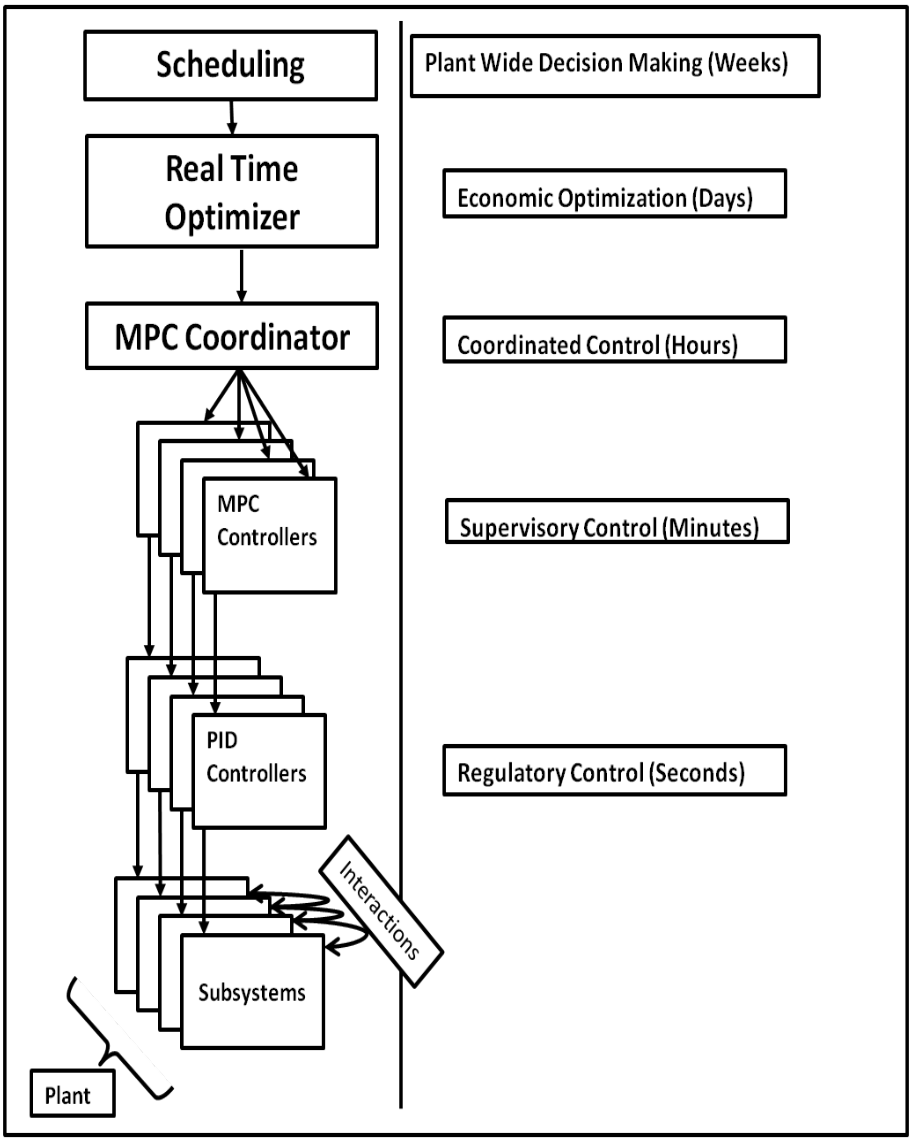

Fig. 2.1. Hierarchical Control Structure.

predict future system behavior. At each time instant, past and current measurements and inputs are used to estimate the state of the system. The future trajectory of inputs are optimized over a control horizon to ensure that the evolution of the outputs and states over a prediction horizon track a desired setpoint. The first input move is implemented and at the next time instant, the input trajectory is re-optimized with the additional available measurements included in the problem as depicted in Fig. 2.2 (adapted from Seborg et al. (2010)). These MPC controllers can be implemented in either a centralized or decentralized fashion. In a centralized strategy, a single monolithic controller is employed to manage the entire network of interconnected subsystems. While centralized MPC leads to plant wide optimum, the centralized optimization problem is computationally intensive, relatively difficult to implement, tune and maintain, and is characterized by poor fault tolerance (Ho (2005)). Also, along with the computational difficulties, a centralized strategy is often plagued with organizational and operational issues. A significant amount of effort is required to collect, handle and process data in centralized fashion. On the other hand, the MPC controllers can be implemented in a decentralized fashion (Sandell et al. (1978)) with individual controllers defined for every subsystem or a smaller network of subsystems. While this makes the controllers more flexible, reliable and easier to implement and maintain, it also leads to solutions that are not plant-wide optimum (Kariwala (2007)). Centralized and decentralized controllers define the limiting extremes of controller design.

MPC technology has been implemented on large-scale industrial applications since the 1980s. Qin *et al* presented a survey of industrial applications of the MPC technology based on linear models (Qin & Badgwell (1997)) and nonlinear models (Qin & Badgwell (2000)). According to their survey, More than 90% of industrial implementations of multivariable control solutions employed some form of MPC. Morari & H Lee (1999) presented a review on the application of MPC for industrial processes with a detailed analysis on the future directions in which industrial research needed to progress. A vendor's perspective was put forth by Kulhavỳ et al.

(2001) through oil refining and heating network case studies. Seki et al. (2001) and Young et al. (2002) investigated the application of MPC to industrial processes such a polymerization and blending processes. Application bottlenecks and implementation issues were described in detail by Ohshima et al. (1995). Finally, a comparative study of the commercially available MPC technologies was presented by Qin & Badgwell (2003).

All large-scale networked systems are characterized by a large number of interactions between the individual subsystems and these interactions have an influence on the local control decisions and overall plant-wide optimality. In most systems/plants, neglecting these interactions or inadequately coordinating the subsystems will, in general, lead to suboptimal performance and even instability of the process. The performance deterioration of decentralized control (Cui & Jacobsen (2002)) as compared to centralized control is due to the interaction between subsystems being inadequately modeled in the decentralized control algorithms. Over the past few years, with the necessity to control large-scale systems efficiently and optimally, distributed and coordinated control structures have been developed to address the shortcomings of both the control paradigms (Siljak & Zecevic (2005)). To achieve optimum plant operation, decentralized controllers have to be coordinated and driven towards achieving the performance of a centralized controller (Jia & Krogh (2001)). This calls for the design of robust coordinators (Aske et al. (2008)) that provide a dynamic performance equivalent to that of a centralized control scheme while maintaining the existing decentralized structure. While each layer of the control architecture should be carefully designed, current research is oriented towards designing robust and computationally feasible coordination layers.

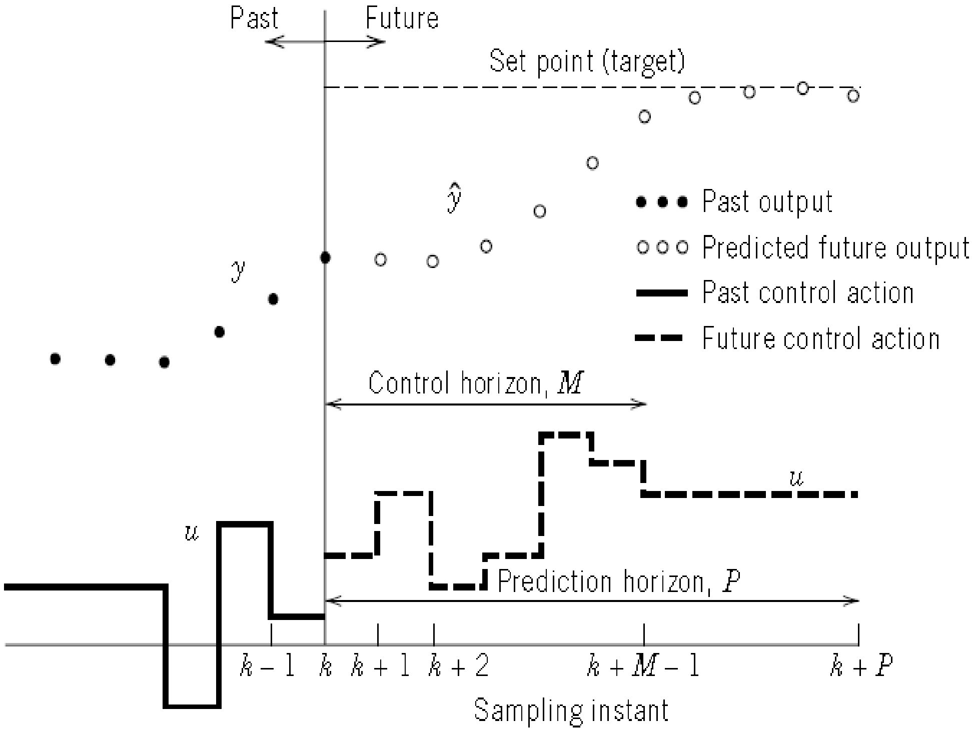

Fig. 2.2. Model Predictive Control

2.3 Coordinating Multiple Model Predictive Controllers

Coordinated MPC (C-MPC) works toward combining the advantages of both the centralized and decentralized control strategies while addressing their respective drawbacks (Venkat et al. (2007)). The decentralized structure of the system is maintained but the performance is driven towards that of a centralized scheme (Negenborn, van Overloop, Keviczky & Schutter (2009), Negenborn et al. (2010)). The coordinator (which is sandwiched between the RTO and the distributed MPC layer) coordinates the actions of the individual MPCs relaying information between the various individual controllers to account for the interaction effects that exist between the different subsystems of the complex large-scale process (Anand et al. (2012)). The coordinator uses information such as states, predicted output trajectory information and calculated control action at each time step to decide the best set of control actions for each individual controller (Camponogara et al. (2002)). There have been a few studies on designing the MPC coordinator originating from different schools of thought (Richards & How (2007), Christofides et al. (2012) and references therein).

Broadly, the coordinated MPC schemes can be categorized as hierarchical, cooperative and non-cooperative coordination strategies. The hierarchical coordination of multiple controllers is one of the earliest coordination methodologies and is described by Mesarovic et al. (1970). In his work, he describes the importance of explicitly accounting for subsystem interactions and coordinating controllers based on predicting the effect of the interactions and balancing out their effects. Based on the principles of interaction balance and interaction prediction, Cheng et al. (2007) and Marcos et al. (2009*a*) developed a methodology to split a centralized control problem dynamically into multiple independent subproblems and coordinated the individual subproblems using the Augmented Lagrangian principle. Mesarovic (1970) describes a hierarchical architecture to control large-scale systems with multiple time scale processes. The upper layer of the control architecture functions on the time scale of the system with the slowest dynamics and the lower layer controllers (working on the systems with fast dynamics) work towards satisfying the long term objectives of the upper layer. Negenborn et al. (2008) described a two layer multi-agent coordination strategy where independent agents negotiated via a negotiator till consensus on the control decision was reached. The application of these algorithms for discrete time system and the efficiency of serial and parallel implementations were described and the utility of multi-agent coordination for transportation and power networks was described in Negenborn et al. (2006) and Negenborn et al. (2007).

An alternative to hierarchical control is the coordination of independent decentralized controllers working in parallel. The coordination algorithm aims to utilize the interaction models that decentralized controllers ignore and enable efficient communication between controllers to achieve plant-wide optimality. The coordinated control algorithms are classified as cooperative and non-cooperative algorithms based on the objective function used by the individual controllers as described by Venkat et al. (2006). The cooperative and non-cooperative coordination algorithms are further classified into iterative and non-iterative strategies based on the communication scheme being implemented. If information between controllers is exchanged only once at every time step, the algorithm is said to be non-iterative. Most of the non-cooperative algorithms are non-iterative, with only a single communication exchange at each time step.

Other works on non-cooperative coordination include Camponogara et al. (2002), which studied the coordination of discrete time linear systems with stability constraints. Richards & How (2007) proposed a sequential non-cooperative coordination method. In his work, each controller waited for the control decision from the previous controller and only once it received the set of input trajectories did it calculate its own control sequence. Jia & Krogh (2001) developed a coordinated control scheme for linear systems coupled only through the state. This work was extended by Dunbar (2007) to dynamically coupled and decoupled systems. This non-cooperative control scheme guarantees stability by including compatibility constraints to ensure deviations from communicated control trajectories is minimized. Keviczky et al. (2006) developed a non-cooperative coordination algorithm for dynamically decoupled systems with only constraint and cost function coupling. In this work, local controllers communicate only with a few neighboring controllers and not the entire network of controllers and this methodology finds application in the coordination of autonomous vehicle swarms. Non-cooperative coordination schemes guarantee closed-loop stability only for systems with weak interactions.

Venkat et al. (2006) describes an iterative procedure to communicate calculated control trajectories between controllers in order to coordinate them. However, each individual controller has a well-defined model and cost function that governs its functioning. However the individual objectives of each subsystem are often in conflict. Since each controller aims to achieve its local goals, the controllers compete with one another resulting in a Nash equilibrium and the converged solution could compromise the closed loop stability of the system. In order to avoid the competition between controllers and to ensure cooperation among them, the authors proposed a modification of the local objectives into a single unified objective. In the cooperative coordination, each controller explicitly accounts for the effects of its inputs on the entire system through the use of a common global cost function. At each iteration, each controller optimizes its own set of inputs based on the control trajectory inputs from the other controllers in the network and the iterative exchange is continued till convergence. The developed coordination algorithm has the advantage of computing a feasible and closed-loop stable solution at every iterate.

Since a feasible solution is computed at every iterate, it enables control practitioners to terminate the coordination algorithm at any iteration based on available computational resources. Irrespective of the limit on the number of iterations, the resulting performance is always better than a decentralized control strategy. It was also proved that the cooperative coordination algorithm would iteratively converge to the centralized controller performance. This work was extended by Stewart et al. (2011) to nonlinear systems, and properties such as feasibility, closed-loop stability and convergence were theoretically proved. Zhang & Li (2007) developed an iterative cooperation-based coordination algorithm for unconstrained systems with communication delays. Liu et al. (2009) and Liu et al. (2010) described a sequential and iterative, cooperative coordination algorithms for nonlinear systems. However, the lyapunov based methodology does not guarantee convergence to the centralized MPC performance due to the non-convexity of the optimization problem.

2.4 Minimum Information Exchange Based Coordinated Model Predictive Control

There have been a few studies on C-MPC strategies originating from different schools of thought and in the last few years there have been few comprehensive comparisons between the various C-MPC strategies (Alvarado et al. (2011) and Christofides et al. (2012)). However, most of the literature on C-MPC has been derived based on the assumption that all subsystem interactions are equally important. A coordinator designed in such a manner is computationally very intensive and can coordinate the individual MPCs only when information from every one of the subsystems is available. There have been a few studies on the selective coordination of subsystems with their neighbors rather than the entire network (Keviczky et al. (2008)). Farina & Scattolini (2011) developed a non-cooperative coordinated control scheme with only neighbor-to-neighbor communication and established convergence properties under mild assumptions on the existence of a suitable decentralized auxiliary control law. Maestre et al. (2009) developed a distributed control architecture for the coordination of multiple controllers with limited information regarding the states and models being exchanged. A game theory based approach was used to ensure cooperation between controllers and the robustness of the developed algorithm was illustrated through the extensive simulations. Schuler et al. (2010) developed a methodological framework to improve the performance of decentralized controllers by selectively including a few interaction models in each of the local control problems. However, there is a dearth of literature on the design of MPC coordinators that prioritize the various interactions and coordinates the individual MPCs based on the relative significance of interactions. Such a strategy, will be able to lead to near plant-wide optimal performance with a significantly lesser computational burden. The need of the hour is to design C-MPC algorithms with minimum information exchange between the local controllers such that the degree of decentralization is maximized while at the same time the performance degradation is minimized. In this sense, the controller topology (interaction structure) is first optimized and then the local controllers are selectively coordinated.

Many methods have been proposed in the literature for analyzing and quantifying the interactions between subsystems in a large-scale system. One of the earliest developed interaction index was the relative gain array (RGA, Bristol (1966)) which utilized the steady state gains of a system to quantify interactions between input-output pairs. Since the introduction of RGA, several modifications of the RGA such as the effective relative gain array (ERGA, Xiong et al. (2006)), dynamic relative gain array (DRGA, Jiang et al. (2012)), dynamic block relative gain array (DBRGA, Kariwala et al. (2003)), relative normalized gain array (RNGA, He et al. (2009)), performance relative gain array (PRGA, Hovd & Skogestad (1992)), etc. These modified interaction indices were developed to address the short comings of the RGA which was based on the steady state properties of the system. These methods presented a more generalized interaction quantifier as they were capable of exploiting the system dynamics and closed loop properties. Apart from the RGA based interaction indices, grammian based interaction quantifiers such as the hankel interaction index array (HIIA, Birk & Medvedev (2003)) and passivity based indices (Bao et al. (2007)) have also been developed. The numerous interaction analyses methods have been designed for various purposes such as control loop pairing, controllability measure, uncertainty analyses, etc. While these interaction measures and their utility have been well established, there have very few studies on the relation between these interaction measures and the performance of coordinated control algorithms. Moreover, the utilization of interaction measures for minimizing the information exchange has not been established and the identification of interaction quantifiers that enable the *a priori* selection of optimal communication architectures would significantly improve the efficiency of C-MPC architectures with iterative communication.

2.5 Coordinating Multiple Model Predictive Controllers for Multi-Reservoir Management

Water is not as bountiful as it was in the last century and is rapidly becoming a scarce commodity. The growing world population is leading to a greater demand for the already depleting natural resources (Zoppou (2001)) and the current climate change scenario is making this worse (Brown et al. (2011)). Droughts, storms and mismanagement of available water supplies are adversely affecting the drinking and irrigation water supply. Moreover, with the sharply increasing oil prices, hydroelectricity is becoming a very lucrative alternative. Water reservoirs are being constructed worldwide to form integrated networks that can provide water for irrigation, consumption and also be used to generate energy (van de Meene et al. (2011)). These large multipurpose reservoirs are generally spread across vast areas and developed as systems of connected reservoirs. The optimal operation of these systems is a challenging task, because of their large dimensionality, the simultaneous presence of multiple and conflicting water users, the non-linearities in the model of the system, and the uncertainties associated to the inflow processes. The need of the hour is thus the development of integrated operational strategies for large, water reservoir networks.

Despite being largely adopted in the process engineering community (Rantzer (2009)), coordination algorithms have not been extensively studied or utilized in the water resources management (Niewiadomska-Szynkiewicz et al. (1996)) field. The use of coordinated control schemes is limited to the management of irrigation canals (Cardona et al. (1997), Negenborn, van Overloop & De Schutter (2009) and Negenborn, van Overloop, Keviczky & Schutter (2009)), while only Niewiadomska-Szynkiewicz et al. (1996) has considered the problem of coordinating multiple controllers for water reservoir networks operation. The control of multi-objective multi-reservoirs are plagued by the large dimensionality of these systems. Also, the strong nonlinearities in the models of the various subsystems, prevent the adoption of an integrated centralized control strategy (Castelletti et al. (2008)). Furthermore, the large water networks are often spread across multiple states and countries with different regulation authorities governing the individual subsystems. This is also one of the main hindrances preventing the adoption of centralized controllers (Pianosi & Galelli (2010)) and consequently results in the adoption of decentralized control strategies, which neglect the interactions between the sub-systems and can easily lead to a sub-optimal performance (Pianosi & Soncini-Sessa (2009) and Schwanenberg et al. (2011)). These large networks consisting of a number of interconnected reservoirs with multiple control objectives, makes the implementation of coordinated MPC strategies a challenging task. However, the implementation of coordinated MPC provides a solution for improving the existing operational procedures, thus providing better in-demand delivery of water and also simultaneously optimizing the pump schedule resulting in significant cost savings. The current state-of-the-art in multi-objective multi-reservoir management systems has been discussed by (Labadie 2004) and the lack of literature on coordinating multiple controllers for water management systems is well documented.

2.6 Summary

Large-scale systems that are formed by a network of interconnected heterogeneous subsystems are quite hard to control and various methodologies have been proposed and investigated over the last few decades. Over the last decade, the control systems for such large-scale systems are often designed as a hierarchical structure with different objectives being addressed at each level of the hierarchy. While most of the layers have been well researched, the current focus is oriented towards designing the MPC coordination layer and developing a robust methodology to integrate the decisions between layers. MPC is a popular supervisory control method which has found large-scale application in the chemical and process engineering industry since the 1980s. There has also been a lot of research on both the theoretical as well as the application oriented development of MPC strategies for large-scale industrial systems. Over the past few years, with the necessity to control large-scale systems efficiently and optimally, research has been focused on developing distributed and coordinated control structures. This has led to the development of MPC coordination schemes stemming from different schools of thought and the current research is oriented towards investigating the applicability of the developed control schemes for real world systems. One such area that has recently received a lot interest is the optimization of communication topologies in coordinated MPC schemes. Despite being largely investigated in process engineering problems, coordinated MPC schemes have been poorly adopted in the water resources management systems. Theses large-scale systems would greatly benefit from the application of a coordinated MPC strategy.

Chapter 3

COORDINATING MULTIPLE MODEL PREDICTIVE CONTROLLERS

3.1 Introduction

Early formulations of coordinated MPC in literature are based on the assumption that exchange (communication) of predicted trajectory information between subsystems is sufficient to account for interactions. It has been demonstrated that exchanging only interaction information among the subsystem controllers is not adequate to guarantee closed loop stability (Rawlings & Stewart (2008)). This instability arises due to the contest between the local controllers as will be seen in the subsequent subsection. In addition to the communication of information, there needs to be cooperation between the controllers (Liu et al. (2009)). A need to modify the objective functions as well as to incorporate interaction models into the local subsystem model arises. Such observations are the basis of coordination strategies. The main tasks of the coordinator are to provide information (such as states, predicted output trajectory and calculated control action at each time step) to controllers enabling them to derive interaction factors (the effect of one subsystem on the other) and also to modify the local optimization problem such that the coordinated performance of the local optimization problems is driven towards the performance of the centralized global optimization problem (Goal Coordination) (Scheu & Marquardt (2009)).

Two common strategies used for coordinator design are (Mesarovic et al. (1970)):

1. Interaction Prediction Principle

2. Interaction Balance Principle

The Interaction Balance Principle includes the interaction variables in addition to the input variables in the manipulated variable set of the local controllers and then the coordinator works towards balancing the error between the desired (calculated) and real interaction variables. On the other hand, the Interaction Prediction Principle considers only the input variables in the manipulated variable set and then the coordinator works towards calculating the correct input variables after predicting and accounting for the effects of the interactions. These principles are fundamental to developing a coordinator for multiple MPCs and these form the basis of all coordination techniques derived in literature. In our work, the popular coordination techniques that have been evaluated are the Communication Based MPC Coordination, Cooperation Based MPC Coordination (Rawlings & Stewart (2008)) and Price Driven MPC Coordination (Cheng et al. (2007)). The work presented in this chapter is based on the techniques developed in literature, but the algorithms have been reformulated extensively to make them applicable to systems described by transfer functions (the original works are based on state-space formulations).

3.2 Coordinated Model Predictive Control

Consider a large scale MIMO system comprised of M individual subsystems. The discrete transfer function matrix formulation of the system, where $\tilde{y}$ denotes the output variable vector and $\tilde{u}$ denotes the manipulated variable vector and $\tilde{d}$ denotes the measured disturbance vector (the dimensions of which are (1xM)) is as follows:

$$\tilde{y} = \tilde{G}_p\tilde{u} + \tilde{G}_d\tilde{d} \tag{3.1}$$

where the process transfer function matrix $\tilde{G}_p$ is defined as,

$$\tilde{G}_p = \begin{bmatrix} G_{11}(z) & G_{12}(z) & . & . & G_{1M}(z) \\ G_{21}(z) & G_{22}(z) & . & . & G_{2M}(z) \\ . & . & . & . & . \\ . & . & . & . & . \\ G_{M1}(z) & G_{M2}(z) & . & . & G_{MM}(z) \end{bmatrix} \tag{3.2}$$

and the disturbance transfer function matrix $\tilde{G}_d$ is defined as,

$$\tilde{G}_d = \begin{bmatrix} G_{d1}(z) & 0 & . & . & 0 \\ 0 & G_{d2}(z) & . & . & 0 \\ . & . & . & . & . \\ . & . & . & . & . \\ 0 & 0 & . & . & G_{dM}(z) \end{bmatrix} \tag{3.3}$$

also,

$$\tilde{y} = \begin{bmatrix} y_1(z) & y_2(z) & . & . & y_M(z) \end{bmatrix} \tag{3.4}$$

$$\tilde{u} = \begin{bmatrix} u_1(z) & u_2(z) & . & . & u_M(z) \end{bmatrix} \tag{3.5}$$

$$\tilde{d} = \begin{bmatrix} d_1(z) & d_2(z) & . & . & d_M(z) \end{bmatrix} \tag{3.6}$$

In the process transfer function matrix $\tilde{G}_p$, the off-diagonal transfer functions represent the interaction models in the system. Each interaction model represents the effect of the input of one subsystem on the output of a different subsystem. For example, $\tilde{G}_{ij}(z)$ is a transfer function model between the input to i-th subsystem and the output of the j-th subsystem.

Without loss of generality, it can be assumed that each subsystem is a SISO system with one measured disturbance each. Each transfer function $\tilde{G}_{ij}(z)$ is equivalent to N_p number of step response coefficients and each $\tilde{G}_{di}(z)$ is equivalent to N_d step response coefficients.

$$G_{ij}(z) \equiv \begin{bmatrix} g_1^{ij} & g_2^{ij} & . & . & g_{N_p}^{ij} \end{bmatrix} \tag{3.7}$$

$$G_{di}(z) \equiv \begin{bmatrix} g_1^{di} & g_2^{di} & . & . & g_{N_d}^{di} \end{bmatrix} \tag{3.8}$$

Let P be the prediction horizon and C the control horizon. The prediction equation for the i-th subsystem will then take the form:

$$\begin{aligned} Y_i = & \left(G_{i1}\Delta u_1 \;+\; G_{i2}\Delta u_2 \;+\; . \;\; . \;+\; G_{iM}\Delta u_M \right) \\ & + \left(F_{i1}x_1 \;+\; F_{i2}x_2 \;+\; . \;\; . \;+\; F_{iM}x_M \right) + (F_{di}x_i) + Y_{iM} \end{aligned} \tag{3.9}$$

where,

$$Y_i = \begin{bmatrix} y_i(t+1) & y_i(t+2) & . & . & . & y_i(t+P) \end{bmatrix}^T \tag{3.10}$$

$$\Delta u_i = \begin{bmatrix} \Delta u_i(t) & \Delta u_i(t+1) & . & . & . & \Delta u_i(t+C-1) \end{bmatrix}^T \tag{3.11}$$

$$\mathrm{x_i} = \begin{bmatrix} \Delta u_i(t-1) & \Delta u_i(t-2) & . & . & . & \Delta u_i(t-N) \end{bmatrix}^T \tag{3.12}$$

$$x_{di} = \begin{bmatrix} \Delta d_i(t-1) & \Delta d_i(t-2) & . & . & . & \Delta d_i(t-\tilde{N}) \end{bmatrix}^T \tag{3.13}$$

Based on the prediction horizon and the model horizon, the number of step response coefficients are,

$$N_p = N + P \tag{3.14}$$

$$N_d = \tilde{N} + P \tag{3.15}$$

The current measurements of the controlled variables are given as:

$$Y_{iM} = \begin{bmatrix} y_{iM}(t) & y_{iM}(t) & . & . & . & y_{iM}(t) \end{bmatrix}^T \tag{3.16}$$

The step response coefficient matrices are as follows:

$$G_{ij} = \begin{bmatrix} g_1^{ij} & 0 & 0 & . & 0 \\ g_2^{ij} & g_1^{ij} & 0 & . & 0 \\ . & . & . & . & . \\ . & . & . & . & . \\ g_P^{ij} & g_{P-1}^{ij} & g_{P-2}^{ij} & . & g_{P-C+1}^{ij} \end{bmatrix} \tag{3.17}$$

$$F_{ij} = \begin{bmatrix} (g_2^{ij} - g_1^{ij}) & (g_3^{ij} - g_2^{ij}) & . & . & (g_{N+1}^{ij} - g_N^{ij}) \\ (g_3^{ij} - g_1^{ij}) & (g_4^{ij} - g_2^{ij}) & . & . & (g_{N+2}^{ij} - g_N^{ij}) \\ . & . & . & . & . \\ . & . & . & . & . \\ (g_{P+1}^{ij} - g_1^{ij}) & (g_{P+2}^{ij} - g_2^{ij}) & . & . & (g_{N+P}^{ij} - g_N^{ij}) \end{bmatrix} \tag{3.18}$$

$$F_{di} = \begin{bmatrix} (g_2^{di} - g_1^{di}) & (g_3^{di} - g_2^{di}) & . & . & (g_{\tilde{N}+1}^{di} - g_{\tilde{N}}^{di}) \\ (g_3^{di} - g_1^{di}) & (g_4^{di} - g_2^{di}) & . & . & (g_{\tilde{N}+2}^{di} - g_{\tilde{N}}^{di}) \\ . & . & . & . & . \\ . & . & . & . & . \\ (g_{P+1}^{di} - g_1^{di}) & (g_{P+2}^{di} - g_2^{di}) & . & . & (g_{\tilde{N}+P}^{di} - g_{\tilde{N}}^{di}) \end{bmatrix} \tag{3.19}$$

The prediction equation may be written as,

$$Y_i(t) = G_{ii}\Delta u_i(t) \ + \ h_i(t) \ + \ l_i(t) \tag{3.20}$$

where,

$$h_i(t) = \sum_{\substack{j=1 \\ j \neq i}}^{M} G_{ij}\Delta u_j(t) \tag{3.21}$$

$h_i(t)$ denotes the effect of future inputs of other subsystems on the i-th subsystem output.

$$l_i(t) = \sum_{j=1}^{M} F_{ij}x_j(t) \ + \ F_{di}x_{di}(t) \ + \ Y_{iM}(t) \tag{3.22}$$

In the above equation, $l_i(t)$ is obtained by summing up the effect of past inputs of all M subsystems (first term), effect of measured disturbances (second term) and current measurements (third term). The prediction equation 3.20 forms the basis of all control calculations.

For each subsystem i, the cost function F_i to be minimized by the local MPC is written in the form:

$$F_i = \sum_{r=1}^{M} w_r J_r(\Delta u_i) \tag{3.23}$$

$$\sum_{r=1}^{M} w_r = 1 \tag{3.24}$$

$$F_i = w_i J_i(\Delta u_i) + \sum_{\substack{r=1 \\ r \neq i}}^{M} w_r J_r(\Delta u_i) \tag{3.25}$$

Here the cost function F_i for the i-th subsystem is the weighted sum of the cost functions J_j of all the M subsystems. For the i-th subsystem the cost function J_i is of the form,

$$J_i = (R_S^i - Y_i)^T \tilde{Q}_i (R_S^i - Y_i) + \Delta u_i^T \tilde{R}_i \Delta u_i \tag{3.26}$$

where R_S^i is a vector of individual subsystem set point R_{Si} defined as:

$$R_S^i = \begin{bmatrix} 1 & 1 & . & . & 1 \end{bmatrix}^T R_{Si} \ (P \ \ terms) \tag{3.27}$$

with,

$$\tilde{Q}_i = q_i I_{PxP} \left(i = \ 1, \ 2, \ . \ . \ ., \ M \right) \tag{3.28}$$

and,

$$\tilde{R}_i = r_i I_{CxC} \left(i = \ 1, \ 2, \ . \ . \ ., \ M \right) \tag{3.29}$$

q_i and r_i are tunable weights and are selected depending on the system dynamics.

For calculating h_i, Δu_j $(j \neq i)$ values, which are the control decisions calculated by the individual MPCs, are assumed to be known. So J_i can be written as,

$$J_i = \frac{1}{2}\Delta u_i^T Q_i \Delta u_i \; - \; \Delta u_i^T C_i \tag{3.30}$$

$$Q_i = G_{ii}^T \tilde{Q}_i G_{ii} \; + \; \tilde{R}_i \tag{3.31}$$

$$C_i = G_{ii}^T \tilde{Q}_i (R_S^i - l_i - h_i) \tag{3.32}$$

The cost function $J_r(\Delta u_i)$ $(r \neq i)$ can be calculated as follows:

$$J_r = (R_S^r - Y_r)^T \tilde{Q}_r (R_S^r - Y_r) \; + \; \Delta u_r^T \tilde{R}_r \Delta u_r \tag{3.33}$$

$$Y_r = G_{rr}\Delta u_r \; + \; h_r \; + \; l_r \tag{3.34}$$

$$h_r = \sum_{\substack{j=1 \\ j \neq r}}^{M} G_{rj}\Delta u_j \tag{3.35}$$

$$l_r = \sum_{j=1}^{M} F_{rj} x_j \; + \; F_{dr} x_{dr} \; + \; Y_{rM} \tag{3.36}$$

Rewriting h_r as,

$$h_r(t) = G_{ri}\Delta u_i(t) \; + \; \sum_{\substack{j=1 \\ j \neq r \\ j \neq i}}^{M} G_{rj}\Delta u_j \; (t) \tag{3.37}$$

$$h_{ri}(t) = \sum_{\substack{j=1 \\ j \neq r \\ j \neq i}}^{M} G_{rj} \Delta u_j \ (t) \tag{3.38}$$

$$\Rightarrow h_r(t) = G_{ri} \Delta u_i(t) \ + \ h_{ri}(t) \tag{3.39}$$

This may be substituted in the cost function 3.33 and $J_r(\Delta u_i)$ is rewritten in the standard form as,

$$J_r = \frac{1}{2} \Delta u_i^T Q_r \Delta u_i \ - \ \Delta u_i^T C_r \tag{3.40}$$

$$Q_r = G_{ri}^T \tilde{Q}_r G_{ri} \tag{3.41}$$

$$C_r = G_{ri}^T \tilde{Q}_r (R_S^r - G_{rr} \Delta u_r - l_r - h_{ri}) \tag{3.42}$$

Writing the cost function F_i

$$F_i = w_i J_i \ + \sum_{\substack{r=1 \\ r \neq i}}^{M} w_r J_r \tag{3.43}$$

In the standard form the cost function is written as

$$F_i = \frac{1}{2} \Delta u_i^T \bar{Q}_i \Delta u_i \ - \ \Delta u_i^T \bar{C}_i \tag{3.44}$$

Substituting Eqs. (3.30)-(3.32) and Eqs. (3.40)-(3.42) in Eq. (3.44), we get

$$\bar{Q}_i = w_i(G_{ii}^T\tilde{Q}_iG_{ii} \ + \ \tilde{R}_i) + \sum_{\substack{r=1 \\ r\neq 1}}^{M} w_r(G_{ri}^T\tilde{Q}_rG_{ri}) \tag{3.45}$$

$$\bar{C}_i = w_iG_{ii}^T\tilde{Q}_i(R_S^i - l_i - h_i) + \sum_{\substack{r=1 \\ r\neq 1}}^{M} w_rG_{ri}^T\tilde{Q}_r(R_S^r - G_{rr}\Delta u_r - l_r - h_{ri}) \tag{3.46}$$

The input rate, input and output constraints for the i-th subsystem are written in the form:

$$\Delta u_i^{\min} \leq \Delta u_i \leq \Delta u_i^{\max} \tag{3.47a}$$

$$u_i^{\min} \leq u_i \leq u_i^{\max} \tag{3.47b}$$

$$y_i^{\min} \leq y_i \leq y_i^{\max} \tag{3.47c}$$

$$\text{for, } i = \ 1, \ \ 2, \ \ . \ \ . \ \ ., \ \ M$$

The input rate constraint Eq. (3.47a) may be rewritten in the form:

$$\begin{bmatrix} -I_{CxC} \\ I_{CxC} \end{bmatrix} \Delta u_i \leq \begin{bmatrix} -\Delta u_i^{\min} \\ \Delta u_i^{\max} \end{bmatrix} \tag{3.48}$$

i.e.

$$M_1^i \Delta u_i \leq N_1^i, \ \ i = \ 1, \ \ 2, \ \ . \ \ . \ \ ., \ \ M \tag{3.49}$$

where,

$$M_1^i = \begin{bmatrix} -I_{CxC} \\ I_{CxC} \end{bmatrix} \; ; \; N_1^i = \begin{bmatrix} -\Delta u_i^{\min} \\ \Delta u_i^{\max} \end{bmatrix} \tag{3.50}$$

Similarly the input constraint Eq. (3.47b) may be reformulated as described below:

$$\begin{bmatrix} u_i(t) \\ u_i(t+1) \\ . \\ . \\ . \\ u_i(t+c-1) \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ . \\ . \\ . \\ 1 \end{bmatrix} u_i(t-1) + \begin{bmatrix} 1 & 0 & 0 & . & . & 0 \\ 1 & 1 & 0 & . & . & 0 \\ . & . & 1 & . & . & 0 \\ . & . & . & 1 & . & . \\ . & . & . & . & 1 & . \\ 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} \Delta u_i(t) \\ \Delta u_i(t+1) \\ . \\ . \\ . \\ \Delta u_i(t+c-1) \end{bmatrix} \tag{3.51}$$

i.e.

$$u_i = c_1 u_i(t-1) + c_2 \Delta u_i \tag{3.52}$$

where,

$$c_1 = \begin{bmatrix} 1 \\ 1 \\ . \\ . \\ . \\ 1 \end{bmatrix} \quad and \quad c_2 = \begin{bmatrix} 1 & 0 & 0 & . & . & 0 \\ 1 & 1 & 0 & . & . & 0 \\ . & . & 1 & . & . & 0 \\ . & . & . & 1 & . & . \\ . & . & . & . & 1 & . \\ 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix} \tag{3.53}$$

$$\Rightarrow \quad M_2^i \Delta u_i \leq N_2^i \tag{3.54}$$

$$M_2^i = \begin{bmatrix} -c_2 \\ c_2 \end{bmatrix} \quad ; \quad N_2^i = \begin{bmatrix} -u_i^{\min} + c_1 u_i(t-1) \\ u_i^{\max} - c_1 u_i(t-1) \end{bmatrix} \tag{3.55}$$

Finally, the output constraint Eq. (3.47c) may be expressed as:

$$M_3^i \Delta u_i \leq N_3^i \tag{3.56}$$

where,

$$M_3^i = \begin{bmatrix} -G_{ii} \\ G_{ii} \end{bmatrix} \quad ; \quad N_3^i = \begin{bmatrix} -y_i^{\min} + l_i + h_i \\ y_i^{\max} - l_i - h_i \end{bmatrix} \tag{3.57}$$

Combining all the three constraints Eqs. (47a, 47b and 47c) for the i-th subsystem, we may write

$$M_i \Delta u_i \leq N_i \tag{3.58}$$

$$M_i = \begin{bmatrix} M_1^i \\ M_2^i \\ M_3^i \end{bmatrix} \quad ; \quad N_i = \begin{bmatrix} N_1^i \\ N_2^i \\ N_3^i \end{bmatrix} \tag{3.59}$$

Method of Quadratic Programming (QP) is used by each local MPC to minimize the cost function defined by Eq. (3.44) subject to the constraints defined by equation Eq. (3.58).

3.2.1 Communication Based Coordination

Every networked system comprises of a number of individual subsystems subject to individual objectives and constraints. Generally, the control algorithms for these subsystems are implemented independently in an iterative manner. In the communication based coordination (Venkat (2006)) strategy, subsystem controllers exchange interaction information at every iteration. Since an MPC optimization scheme is being employed, trajectories for the input variables are available at each iteration and this information is exchanged between the subsystem controllers as illustrated in Fig. 3.1.

Each communication-based MPC transmits the current state and input trajectory information to all interconnected subsystems MPCs through the coordinator. However, each individual controller has no knowledge of the cost functions of other controllers. The objectives of each subsystems MPC controller are frequently in conflict with the objectives of the controllers (MPCs) that control the other interacting subsystems. The equilibrium of such a strategy is driven to a non cooperative equilibrium or Nash equilibrium (Liu et al. (2010)). Due to the non-cooperative and competing effect, such a strategy is usually suboptimal and when interactions are strong, closed loop stability is not guaranteed.

In the communication based coordination strategy, we substitute $w_i = 1$ and $w_r = 0 \; \forall \; r \neq i$ in Eqs. (3.43), (3.45) and (3.46) as each local MPC optimizes its own independent objective. This leads to:

$$\bar{Q}_i = G_{ii}^T \tilde{Q}_i G_{ii} \; + \; \tilde{R}_i \tag{3.60}$$

$$\bar{C}_i = G_{ii}^T \tilde{Q}_i (R_S^i - l_i - h_i) \tag{3.61}$$

where,

$$h_i = \sum_{\substack{j=1 \\ j \neq i}}^{M} G_{ij} \Delta u_j \tag{3.62}$$

and

$$l_i = \sum_{j=1}^{M} F_{ij} x_j \; + \; F_{di} x_{di} \; + \; Y_{iM} \tag{3.63}$$

The controllers now solve the optimization problem defined in Eqs. (3.43) and (3.58) using the values derived for $\bar{Q}_i$ and $\bar{C}_i$ in Eqs. (3.60) and (3.61).

The local controllers are exchanging interaction information through the modified prediction equation (Eqs. (3.62) and (3.63)) but, they optimize different individual objective functions and these independent objective functions may often be conflicting in nature. As a result, despite having knowledge of the local control decisions, the individual controllers try to achieve their own individual optima. In other words, the controllers are working with the same resources (control variables) but towards satisfying different objectives leading to a contest between the individual controllers. As a result, when the interactions are strong, the individual controllers fail to converge to a single optimal control decision. This drives the equilibrium of such a strategy towards a non-cooperative equilibrium (Anand et al. (2010, 2011), Venkat (2006)).

3.2.2 Cooperation Based Coordination

The cooperation based coordination strategy works toward improving the performance of an existing decentralized control structure by allowing the subsystem controllers exchange interaction information and also support each other in driving the performance towards that of a centralized controller (Stewart et al. (2011)). To overcome the drawbacks associated with communication based coordination strategies (non-cooperative and competing controllers), the following modification has been incorporated in the cooperation based coordination strategy:

- The local objective functions of each subsystem MPC controller are converted to a common global objective function. This is achieved by using a weighted convex sum of the individual objective functions as the new objective function as indicated in Eqs. (3.64), (3.65) and (3.66) and also illustrated in Fig. 3.1.

$$F_i = \sum_{r=1}^{M} w_r J_r(\Delta u_i) \tag{3.64}$$

$$\sum_{r=1}^{M} w_r = 1 \tag{3.65}$$

$$F_i = w_i J_i(\Delta u_i) \ + \sum_{\substack{r=1 \\ r \neq i}}^{M} w_r J_r(\Delta u_i) \tag{3.66}$$

Weights w_r and w_i are assigned to the various objectives heuristically based on the physical or economic significance of the variables being optimized/controlled at each subsystem. Subsystems or output variables that have a more significant effect on the overall plant operations as designated by the process engineer would be weighed more significantly than the others. In our studies, we have weighed all objectives equally in the cooperation based coordination strategy. The control problem derived in Eqs. (3.23) to (3.59) are solved to determine the optimal control profile. Since all the local MPC controllers are solving an optimization problem with the same objective function, the optimal control profile generated at all iterates of the cooperative based coordination is plant-wide feasible and closed loop stable (Pareto Optimal) (Maestre et al. (2010)). To improve the rate of convergence, Wegstein's Method (Wegstein (1958)) is employed during the iterative communication process.

In the iterative cooperative cooordination architecture, at any iteration i, a set of control moves (over the control horizon) is available for each local controller k: $\Delta u^k{}_i$. In order to accelerate the convergence, the control moves from the current and previous iteration are used to calculate an approximation of the next set of control moves and this leads to accelerated convergence (see Appendix A for details).

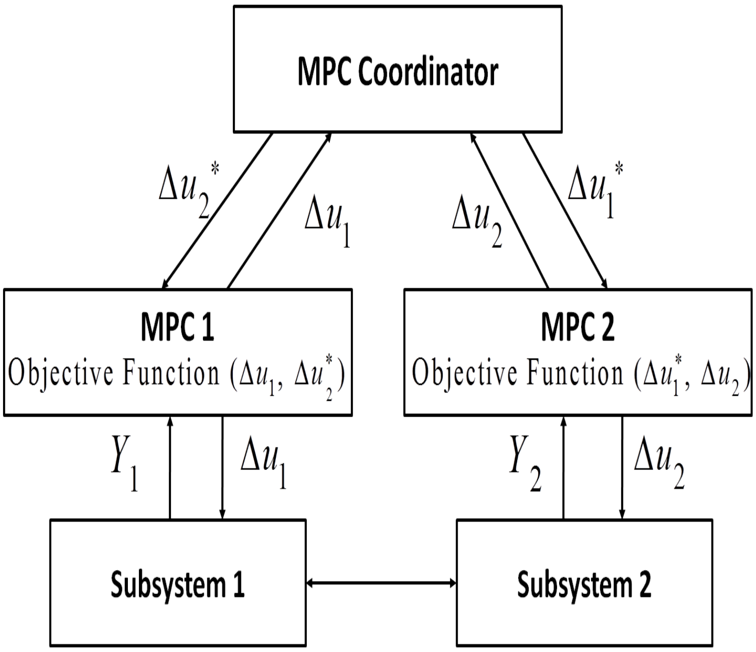

Fig. 3.1. Schematic of Communication and Cooperation Based MPC Coordination.

3.2.3 Price Driven Coordination

One other technique used for coordinating multiple MPC controllers is based on separating the centralized optimization problem into a number of disjoint, independent sub problems (Cheng et al. (2007, 2008)). This is brought about by the addition of auxiliary variable to the decision variable set. The objective functions are rewritten in terms of the Lagrange multipliers and the Lagrange multipliers are iteratively adjusted to satisfy the constraints. In the price driven coordination strategy (Marcos et al. (2009*a*,*b*)), the large-scale system is decomposed into a number of subsystems based on the principle of separability. Fig. 3.2 illustrates the price driven coordination scheme. Auxiliary variables (e_i) in the form of price vectors (v_i) and resource constraints Eq. (3.68) are introduced to the existing control problem. The optimum plant performance is obtained by equating the total demand from all subsystems to overall resource availability (Lasdon (1968), Rantzer (2009)). The price vector is iteratively adjusted till the constraints are satisfied. Newton′s algorithm is used to adjust the price vector iteratively.

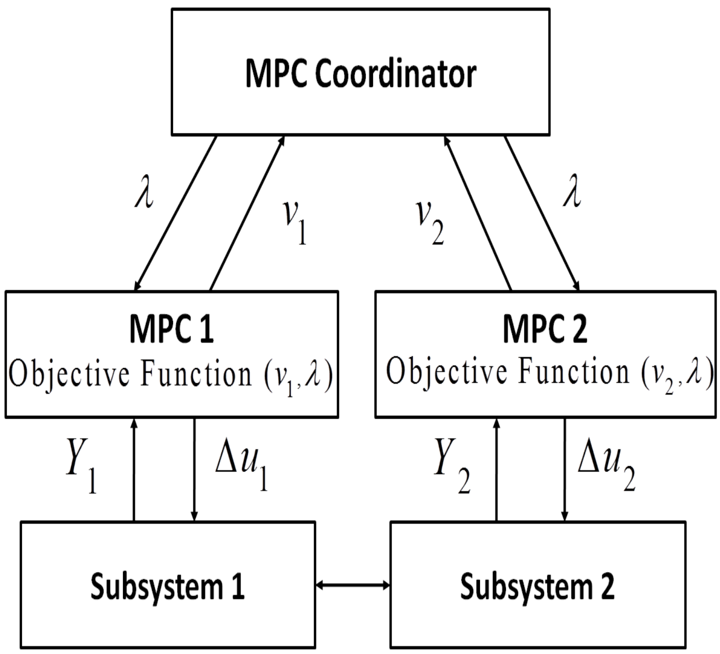

Fig. 3.2. Schematic of Price Driven MPC Coordination.

By introducing an auxiliary variable e_i, the prediction equation, Eq. (3.20) is rewritten as:

$$Y_i(t) = G_{ii}\Delta u_i(t) + e_i(t) + l_i(t) \tag{3.67}$$

The $'linking\ constraint'$ or the $'resource\ constraint'$ is given by Eq. (3.68)

$$e_i(t) - \sum_{\substack{j=1 \\ j\neq i}}^{M} G_{ij}\Delta u_j = 0 \tag{3.68}$$

Next we define an auxiliary vector v_i as

$$\begin{aligned} v_i &= \begin{bmatrix} \Delta u_i^T & e_i^T \end{bmatrix}^T \\ &= \begin{bmatrix} \Delta u_i(t) & . & . & \Delta u_i(t+C-1) & e_i(t+1) & . & . & e_i(t+P) \end{bmatrix}^T \end{aligned} \tag{3.69}$$

Now,

$$Y_i(t) = \tilde{G}_{ii}v_i \; + \; l_i \tag{3.70}$$

where,

$$\tilde{G}_{ii} = \begin{bmatrix} G_{ii} & I_{PxP} \end{bmatrix} \tag{3.71}$$

Now the global objective function is written as a sum of M disjoint objective functions corresponding to the individual subsystems.

$$J = \sum_{i=1}^{M} J_i(v_i) \tag{3.72}$$

$$J_i(v_i) = (R_S^i - Y_i)^T \tilde{Q}_i (R_S^i - Y_i) \ + \ v_i^T \bar{R}_i v_i \tag{3.73}$$

where,

$$\bar{R}_i = \begin{bmatrix} \tilde{R}_i & 0 \\ 0 & R_i I_{PxP} \end{bmatrix} \tag{3.74}$$

Now,

$$J_i(v_i) = \frac{1}{2} v_i^T Q_i v_i - v_i C_i \tag{3.75}$$

where,

$$Q_i = \tilde{G}_{ii}^T \tilde{Q}_i \tilde{G}_{ii} + \bar{R}_i \tag{3.76}$$

$$C_i = \tilde{G}_{ii}^T \tilde{Q}_i (R_S^i - l_i) \tag{3.77}$$

Rewriting the resource constraint,

$$e_i - \sum_{\substack{j=1 \\ j \neq i}}^{M} G_{ij} \Delta u_j = \bar{O} \tag{3.78}$$

where,

$$\bar{O} = \begin{bmatrix} 0 & 0 & . & . & 0 \end{bmatrix}_{P\,times}^T \tag{3.79}$$

Expanding 3.78, we may write

$$
\begin{aligned}
&e_1 - G_{12}\Delta u_2 - G_{13}\Delta u_3 - \quad . \quad . \quad . - \; G_{1M}\Delta u_M &= 0\\
&e_2 - G_{22}\Delta u_2 - G_{23}\Delta u_3 - \quad . \quad . \quad . - \; G_{2M}\Delta u_M &= 0\\
&e_3 - G_{32}\Delta u_2 - G_{33}\Delta u_3 - \quad . \quad . \quad . - \; G_{3M}\Delta u_M &= 0\\
&.\\
&.\\
&.\\
&e_M - G_{M2}\Delta u_2 - G_{M3}\Delta u_3 - \quad . \quad . \quad . - \; G_{MM}\Delta u_M &= 0
\end{aligned}
\tag{3.80}
$$

Eq. (3.80) may be regrouped as,

$$\begin{bmatrix} O_{PxC} & I_{PxP} \\ -G_{21} & O_{PxP} \\ -G_{31} & O_{PxP} \\ . & . \\ . & . \\ . & . \\ -G_{M1} & O_{PxP} \end{bmatrix} \begin{bmatrix} \Delta u_1 \\ e_1 \end{bmatrix} + \begin{bmatrix} -G_{12} & O_{PxP} \\ O_{PxC} & I_{PxP} \\ -G_{32} & O_{PxP} \\ . & . \\ . & . \\ . & . \\ -G_{M2} & O_{PxP} \end{bmatrix} \begin{bmatrix} \Delta u_2 \\ e_2 \end{bmatrix} + \ . \ .$$

$$. \ . + \begin{bmatrix} -G_{1M} & O_{PxP} \\ -G_{2M} & O_{PxP} \\ -G_{3M} & O_{PxP} \\ . & . \\ . & . \\ . & . \\ O_{PxC} & I_{PxP} \end{bmatrix} \begin{bmatrix} \Delta u_M \\ e_M \end{bmatrix} = \begin{bmatrix} \bar{O}_{Px1} \\ \bar{O}_{Px1} \\ \bar{O}_{Px1} \\ . \\ . \\ . \\ \bar{O}_{Px1} \end{bmatrix} \tag{3.81}$$

which may be written as,

$$\sum_{i=1}^{M} A_i v_i = \bar{O} \tag{3.82}$$

The constraints are,

$$\Delta u_i^{\min} \leq \Delta u_i \leq \Delta u_i^{\max} \tag{3.83a}$$

$$u_i^{\min} \leq u_i \leq u_i^{\max} \tag{3.83b}$$

for, $i = i,\ 2,\ \ldots,\ M$

$$-A \leq e_i \leq A \ \ ; \ \ i = 1,\ 2,\ ....,\ P \tag{3.84}$$

In terms of v_i,

$$M^i v_i \leq N^i \tag{3.85}$$

where,

$$M^i = \begin{bmatrix} M_1^i & 0_{2CxP} \\ M_2^i & 0_{2CxP} \\ 0_{PxC} & -I_{PxP} \\ 0_{PxC} & I_{PxP} \end{bmatrix} \ ; \ N^i = \begin{bmatrix} N_1^i \\ N_2^i \\ \alpha_{Px1} \\ \alpha_{Px1} \end{bmatrix} \tag{3.86}$$

$$M_1^i = \begin{bmatrix} -I \\ I \end{bmatrix} \ ; \ N_1^i = \begin{bmatrix} -\Delta u_i^{\min} \\ \Delta u_i^{\max} \end{bmatrix} \tag{3.87}$$

$$M_2^i = \begin{bmatrix} -c_2 \\ c_2 \end{bmatrix} \ ; \ N_1^i = \begin{bmatrix} -u_i^{\min} + c_1 u_i(t-1) \\ u_i^{\max} - c_1 u_i(t-1) \end{bmatrix} \tag{3.88}$$

In summary, the optimization problem is posed as,

$$Min \qquad J(v) = \sum_{i=1}^{M} J_i(v_i)$$

$$Subject\ to$$

$$M^i v_i \leq N^i \tag{3.89}$$

$$and$$

$$\sum_{i=1}^{M} A_i v_i = \bar{O}$$

Using Lagrange multipliers (price vectors), the optimization problem is solved for the i-th subsystem,

$$\begin{gathered} g_i(\lambda) = min \ \ \tfrac{1}{2} v_i^T Q_i v_i - v_i^T \tilde{C}_i \\ subject\ to \quad M^i v_i \leq N^i \ \ ; \ \ i = 1,\ 2,\ ....,\ M \end{gathered} \tag{3.90}$$

where,

$$Q_i = \left[\tilde{G}_{ii}^T \tilde{Q}_i \tilde{G}_{ii} + \bar{R}_i \right] \tag{3.91}$$

$$\tilde{C}_i = C_i - A_i^T \lambda \tag{3.92}$$

$$C_i = \left[\tilde{G}_{ii}^T \tilde{Q}_i (R_S^i - l_i) \right] \tag{3.93}$$

λ (in Eq. (3.90)) is adjusted using Newton′s algorithm till convergence ($g^k = 0$),

$$\lambda^{k+1} = \lambda^k - \alpha_k g^k \tag{3.94}$$

where, g^k is the gradient of $\sum_{i=1}^{M} A_i v_i$ and k is the iteration number.

Note that I_{AxA} is used to denote an identity matrix of dimension AxA and O_{AxB} is used to denote a matrix of zeros of dimension AxB.

3.3 Case Studies

In order to analyze and evaluate the performance of the coordination strategies, the results from two systems (a generic benchmark system and a quadruple tank system) which exemplify the nature of the coordination strategies and bring out their uniqueness are provided here. The cases studies described in this work are popular systems developed to benchmark new control strategies. A tuning strategy derived by Shridhar & Cooper (1997) was used to tune the individual multivariable model predictive controllers. The performances of the various control algorithms were investigated and the results are provided and discussed. The performance metric is measured in terms of deviations from set point (sum of squared errors (SSE)). Model predictive controllers based on transfer function models (convolution models) were derived and implemented in MATLAB version 7.8.0.347.

The $Total\ SSE$ which is the sum of the SSE$'$s of all response variables is given as:

$$SSE = \sum_{i=1}^{M} (Y_i - R_S^i)^2 \tag{3.95}$$

3.3.1 Shell Benchmark Problem

The Shell benchmark problem was originally designed as a benchmark for control studies. It is model of a heavy oil fractionator characterized by three side circulating loops and three product draws. The output variables are the compositions at the top and side draws and the reflux temperature while the manipulated variables are the top and side draw rates and also the reflux heat duty. The main objective of this control problem is to maintain the draw compositions at a desired setpoint. The generic benchmark developed by Prett & García (1988) has been used by many researchers for the evaluation of new control strategies. In this work, the model presented by Li et al. (2005) has been utilized and a schematic of the process adapted from Maciejowski (1999) is shown in Fig. 3.3. While the system used in this work has previously been utilized for evaluating various control strategies including MPC, this is one of the first works that has utilized this system for evaluating the performance of a coordinate control strategy. The shell benchmark problem is a multivariable and constrained process with a high level of interactions between the subsystems. This problem is also characterized by input, input rate and output constraints.

The model of the process is: $y = G(s)u + G_d(s)d$ with the transfer function matrices:

$$G(s) = \begin{bmatrix} \frac{4.05e^{-27s}}{50s+1} & \frac{1.77e^{-28s}}{60s+1} & \frac{5.88e^{-27s}}{50s+1} \\ \frac{5.39e^{-18s}}{50s+1} & \frac{5.72e^{-14s}}{60s+1} & \frac{6.90e^{-15s}}{40s+1} \\ \frac{4.38e^{-20s}}{33s+1} & \frac{4.42e^{-22s}}{44s+1} & \frac{7.20}{19s+1} \end{bmatrix} \text{ and } G_d(s) = \begin{bmatrix} \frac{1.44e^{-27s}}{40s+1} \\ \frac{1.83e^{-15s}}{20s+1} \\ \frac{1.26}{32s+1} \end{bmatrix}$$

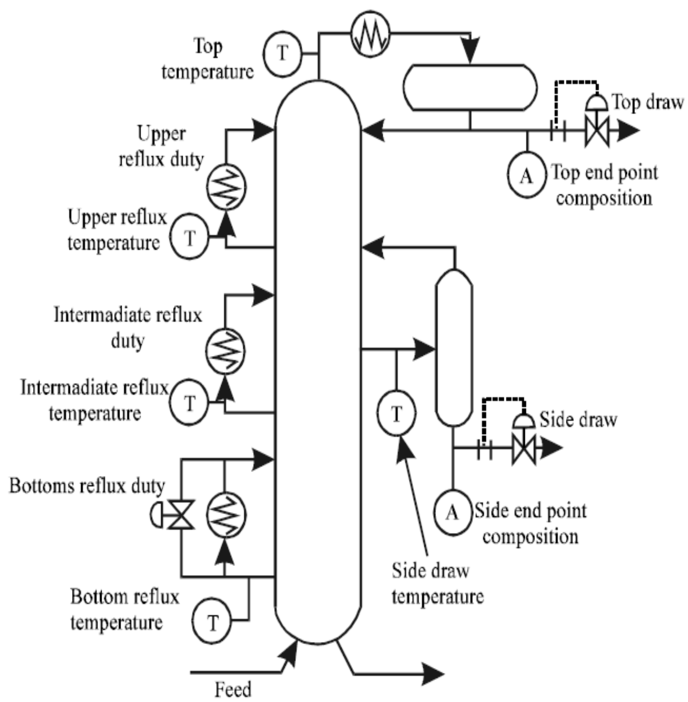

Fig. 3.3. Shell Heavy Oil Fractionator (Adapted from Maciejowski (1999))

The constraints include,

$|y_i| \leq 0.5$, $|u_i| \leq 0.5$, $|\Delta u_i| \leq 0.5$ for $i = 1, 2, 3$

The interactions are quantified using the relative gain array (RGA). The RGA for this system is $\begin{bmatrix} 2.0757 & -0.7289 & -0.3468 \\ 3.4242 & 0.9343 & -3.3585 \\ -4.499 & 0.7946 & 4.7053 \end{bmatrix}$

The presence of significant off-diagonal terms indicates the severe interaction that exists in the system. Simulations indicated that the effect of these interactions were strong and though the decentralized control strategy yielded a closed loop stable solution its performance was significantly degraded as compared to the centralized performance.

The tuned parameters were as follows: prediction horizon = 24, control horizon = 6 and move suppression vector = [15 15 20]. A set point change of magnitude 0.1 was introduced to the three subsystems at sampling instants 10, 20 and 30 respectively. Also, step disturbances of magnitude 0.1 were introduced in the three sub-systems at sampling instants 200, 250 and 300.

In this system, all the coordination strategies were able to provide stable closed loop responses but, with significantly differing performances as shown in Table 3.1 and also seen in Fig. 3.4. The cooperation based coordination algorithm was computationally intensive due to the iterative process involved, but was observed to asymptotically converge to the centralized controller performance as seen in Fig. 3.5. On the other hand, the price driven coordination was able to converge much faster to an improved solution. In Table 3.1, the average number of optimization calls per controller has been provided. Since the simulations were not optimized for computational time, the number of optimization calls is used as a measure of computational intensity. While the centralized MPC invokes the optimization routine only 500 times, the size of the optimization problem is much larger. Whereas all other controller strategies solve optimization problems of the same dimension, making the number of optimization calls a reliable metric for gauging the computational requirements of the different coordination algorithms. As seen, the price driven coordinator requires considerably less computational effort as compared to the cooperation based coordinator and outperforms the other coordination algorithms on a performance per computational effort basis. On the other hand, the cooperation based coordination algorithm produces a feasible solution at every iteration, and hence the number of iterations can be limited as desired. The performance was quantified by the $Total\ SSE$ which is the sum of the SSE′s of all response variables.

Table 3.1
Performance Indices for Shell benchmark case study

Control Algorithm	Total SSE	Average # Optimization Calls per MPC
Centralized MPC	0.097	500
Decentralized MPC	0.604	500
Comm. Based MPC	0.524	2644
Coop. Based MPC (200 iterations)	0.391	9565
Coop. Based MPC (1000 iterations)	0.103	10373
Price Driven MPC	0.183	3290

The main task of the coordinator is to derive the effects of interactions between subsystems. The quantification of these interactions are not straightforward and the exact interaction models may not be estimated accurately in the real world. It is of prime importance to gauge the effect of the mismatches in the interaction models on the performance of the coordinators. This would aid the selection and design of the most robust coordinator for real world applications. This study is more important in a distributed setting as the existing distributed decentralized control configuration would be designed by explicitly ignoring these interaction effects. So the task of estimating the interaction effects to be utilized by the coordinator becomes even more challenging. The robustness of the coordinated control algorithms was studied by introducing model-plant mismatches (Badwe et al. (2009, 2010)) in the interaction models. The communication based strategy does not guarantee stability as

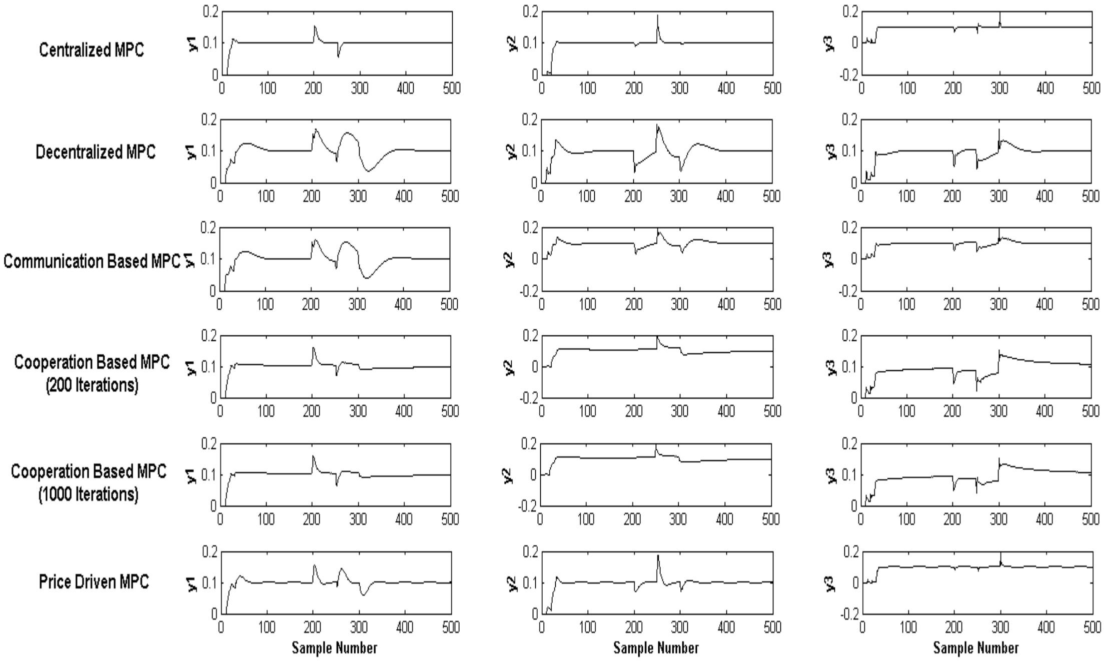

Fig. 3.4. Comparison of the shell oil system output variables' response under different control configurations.

discussed in Section 3.2.1 due to the competition between individual controllers. In order to overcome this drawback, the cooperation based coordination algorithm was developed, and is an extension of the communication based coordination algorithm. The individual objective functions in the communication based coordination strategy were modified into a single unified objective in the cooperation based coordination strategy in order to guarantee stability and convergence. Hence, all further comparisons are only between the cooperation based coordination and price driven coordination strategies. The models used by the MPC controller were modified by varying the gain, dead time and time constants of the off-diagonal terms (interaction models) in the transfer function matrix $G(s)$ utilized by the controllers. The

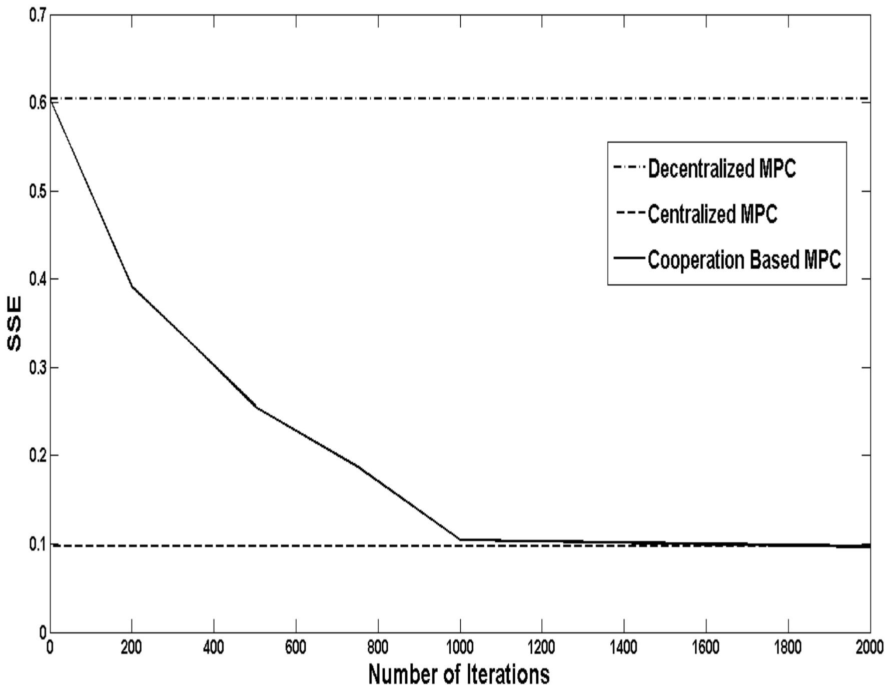

Fig. 3.5. Convergence of Cooperation Based Coordinated MPC to Centralized Performance.

number of interaction models varies polynomially with the number of subsystems in a large-scale system. Also, the effect of the individual interactions could vary quite drastically with some interactions having a significant effect, while the effect of the other interactions could be inconsequential. In order to assess the performance of the coordinator in the presence of model-plant mismatches, a few interaction models were randomly chosen and the transfer function properties were altered. It should be noted that the model-plant mismatches will only affect the performance of the centralized and coordinated MPC control strategies. The decentralized control strategy which doesn't utilize the interaction models will be unaffected by the mismatches. The aim of this study is to quantify the performance deterioration of the C-MPC control strategy in the presence of model-plant mismatches. In the simulation results provided below, mismatches were introduced in the transfer functions G_{12}, G_{23} and G_{31} in $G(s)$. In the presence of mismatches, the performances of the coordination algorithms were quantified based on the *'percent deviation'* which is an indication of how much the uncertainty in the process models affects the performance of any coordination algorithm compared to its performance when there is no mismatch. Higher percent deviation values indicate that the particular coordination algorithm is more sensitive to model-plant mismatches.

$$\% \text{ Deviation} = \left(\frac{\text{SSE}_{\text{NoMismatch}} - \text{SSE}_{\text{With Mismatch}}}{\text{SSE}_{\text{NoMismatch}}} \right) \text{x100} \tag{3.96}$$

Price driven coordination was found to be more robust and deviated less from the base value (no mismatch performance) as seen in Table 3.3, Table 3.4 and Table 3.5. The direction of mismatch, especially in the gain was found to have a significant effect on the controller performance and cooperation based coordination was unable to handle large positive mismatches (overestimated gain values) as seen in Table 3.3. Though the performance of price driven coordination deteriorated in the presence of overestimated gain values, it was still able to converge to a feasible solution and resulted in a stable response. Underestimation of the gains in the interaction models did not have very significant effects on the coordination algorithms performances and price driven coordination was found to deviate less than cooperation based coordination. The trends were seen to be similar for mismatches in gain, dead time and time constants and similar studies were carried out for mismatches in different transfer function models resulting in similar trends.

The applicability of the coordination algorithm for MIMO systems were verified by reconfiguring the Shell Benchmark case study with MIMO controllers. The same system which was previously decomposed into 3 SISO subsystems was now decomposed into a MIMO subsystem and SISO subsystem as depicted below. The upper block matrix represents the first 2 input - 2 output subsystem and the lower block matrix represent the second 1 input - 1 output subsystem.

$$\begin{bmatrix} \begin{bmatrix} \frac{4.05e^{-27s}}{50s+1} & \frac{1.77e^{-28s}}{60s+1} \\ \frac{5.39e^{-18s}}{50s+1} & \frac{5.72e^{-14s}}{60s+1} \end{bmatrix} & \begin{matrix} \frac{5.88e^{-27s}}{50s+1} \\ \frac{6.90e^{-15s}}{40s+1} \end{matrix} \\ \begin{matrix} \frac{4.38e^{-20s}}{33s+1} & \frac{4.42e^{-22s}}{44s+1} \end{matrix} & \begin{bmatrix} \frac{7.20}{19s+1} \end{bmatrix} \end{bmatrix}$$

Two MPC controllers were designed for the system and the simulation results are provided in Table 3.2. It was seen that while the performances of all the algorithms are better than the previously reported SISO control configuration, the relative performance trends of the different coordination algorithms remain the same. The performance improvement over the SISO control configuration is due to the fact that the MIMO subsystem includes two of the previously mentioned interaction models in the system model. As two of the interaction effects are implicitly modeled into the subsystem, the overall performance improves.

Table 3.2
Performance Indices for shell benchmark case study (MIMO Configuration)

Control Algorithm	Total SSE
Centralized MPC	0.097
Decentralized MPC	0.416
Comm. Based MPC	0.377
Coop. Based MPC (200 iterations)	0.231
Coop. Based MPC (1000 iterations)	0.1034
Price Driven MPC	0.163

Table 3.3
Performance Indices in the presence of model-plant mismatch (Gain Mismatch)

Gain Mismatch	SSE for Centralized	% Deviation	SSE for Coop. Based MPC (200 iterations)	% Deviation	SSE for Price Driven MPC	% Deviation
+50%	Unstable	Unstable	Unstable	Unstable	0.782	327.32
+10%	0.138	42.26	0.731	86.95	0.201	9.83
0% (No Mismatch)	0.097	-	0.391	-	0.183	-
-10%	0.102	5.15	0.429	9.72	0.188	2.73
-50%	0.105	8.25	0.443	13.30	0.203	10.93

Table 3.4
Performance Indices in the presence of model-plant mismatch (Dead Time Mismatch)

Dead Time Mismatch	SSE for Centralized	% Deviation	SSE for Coop. Based MPC (200 iterations)	% Deviation	SSE for Price Driven MPC	% Deviation
+50%	0.106	9.27	0.467	19.43	0.207	13.11
+10%	0.099	2.06	0.413	5.63	0.187	2.19
0% (No Mismatch)	0.097	-	0.391	-	0.183	-
-10%	0.099	2.06	0.397	1.53	0.185	1.09
-50%	0.101	4.12	0.416	6.39	0.187	2.19

Table 3.5
Performance Indices in the presence of model-plant mismatch (Time Constant Mismatch)

Time Constant Mismatch	SSE for Centralized	% Deviation	SSE for Coop. Based MPC (200 iterations)	% Deviation	SSE for Price Driven MPC	% Deviation
+50%	0.112	15.46	0.499	27.62	0.216	18.03
+10%	0.101	4.12	0.432	10.49	0.195	6.56
0% (No Mismatch)	0.097	-	0.391	-	0.183	-
-10%	0.099	2.06	0.418	6.91	0.191	4.37
-50%	0.104	7.21	0.457	16.88	0.211	15.30

3.3.2 Quadruple Tank System

The quadruple tank system described in the literature by Alvarado et al. (2011) and Rosinova & Markech (2008) was employed as a simulated test bed for evaluating different coordination strategies. This system is a popular benchmark case study used for the evaluation of new control strategies including MPC and distributed MPC. Alvarado et al. (2011) provides an overview of the experimental performance and the properties of several state-of-the-art distributed predictive controllers on this case study. In this system, it is desired to control the level of water in the lower two tanks (tank 1 and tank 2) using two pumps. The flows from pumps 1 and 2 (v_1 and v_2) are manipulated to control the water levels in the lower tanks 1 and 2 respectively (y_1 and y_2). The outflows from tanks 3 and 4 are the disturbances. γ_1 and γ_2 represent the valve positions that distributes the flow of water between the lower and upper tanks and can be tuned to change the dynamics of the system as seen in 3.6.

In this work, we employ the model of the quadruple tank systemJohansson (2000) in the form: $y = G(s)u + G_d(s)d$ with the transfer function matrices:

$$G(s) = \begin{bmatrix} \frac{3.7*\gamma_1}{62s+1} & \frac{3.7*(1-\gamma_2)}{(62s+1)(23s+1)} \\ \frac{4.7*(1-\gamma_1)}{(30s+1)(90s+1)} & \frac{4.7*\gamma_2}{90s+1} \end{bmatrix} \text{ and } G_d(s) = \begin{bmatrix} \frac{1}{20s+1} \\ \frac{0.5}{30s+1} \end{bmatrix}$$

The constraints are: $|y_i| \leq 5$, $|u_i| \leq 10$, $|\Delta u_i| \leq 1$ for $i = 1, 2$

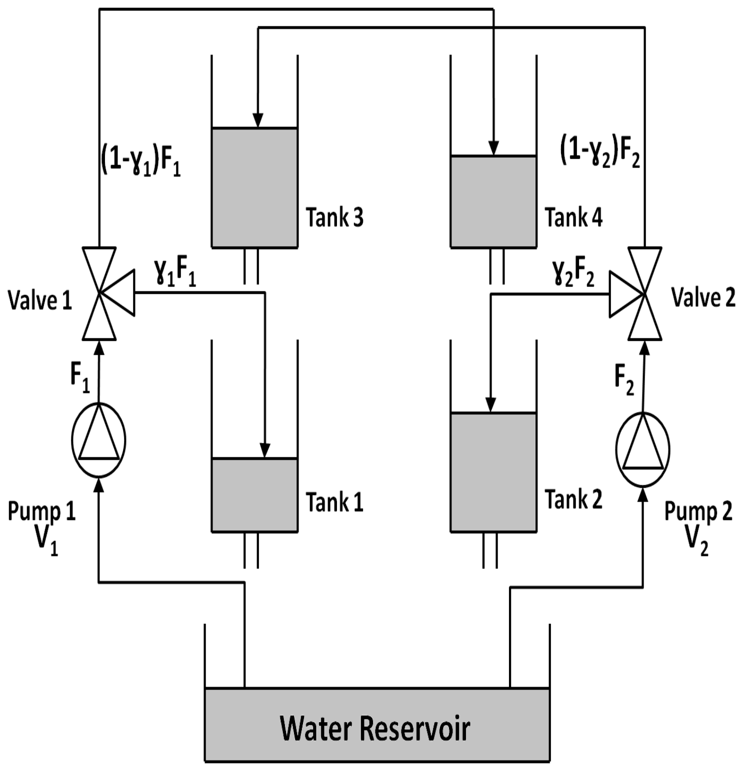

Fig. 3.6. Quadruple Tank System

The RGA for the quadruple tank system is $\begin{bmatrix} 1.0667 & -0.0667 \\ -0.0667 & 1.0667 \end{bmatrix}$ or $\begin{bmatrix} -0.2250 & 1.2250 \\ 1.2250 & -0.2250 \end{bmatrix}$

depending on the value of γ_1 and γ_2 (the former for $\gamma_1 = \gamma_2 = 0.8$ or and the latter for $\gamma_1 = \gamma_2 = 0.3$). This indicates the presence of interacting subsystems and depending on the valve positions (value of γ_1 and γ_2), the interaction effects (off-diagonal terms) become significant and ignoring them leads to severe instabilities. With a valve opening of 0.8 ($\gamma_1 = \gamma_2 = 0.8$), the system exhibits minimum phase characteristics and with a valve opening of 0.3 ($\gamma_1 = \gamma_2 = 0.3$) the system exhibits non-minimum phase characteristics. The system was simulated under both minimum and non-minimum phase characteristics by manipulating the position of the external valve and the different controller coordination algorithms were compared under both the minimum and non-minimum phase scenarios.

The tuned parameters were as follows: prediction horizon = 15, control horizon = 5 and move suppression vector = [0.01 0.01]. The desired water level set points of the two lower tanks were increased by 1 unit at sampling instants 4 and 100. Also, disturbances (Gd) in the form of inflows to the upper level tanks were introduced at sampling instants 150 and 200.

Under minimum phase behavior, all coordination algorithms were able to provide a closed loop stable solution with performances better than a decentralized controller and also close to the centralized controller performance as seen in Table 3.6 and also in Table 3.7. Again, on a performance per computational effort basis, the price driven coordinator was seen to outperform the other coordination algorithms as seen in Table 3.6. This was not the case with a non-minimum phase behavior which was seen to deteriorate the performance of the controllers, making the system harder to control. A non-minimum phase behavior resulted in severe interactions between subsystems and only the cooperation based coordination resulted in a closed loop stable solution while all other coordination strategies failed. The details are summarized in Table 3.7.

Similar to the previous case study, model plant mismatches were introduced to the interaction models to analyze the robustness of the coordination algorithms. The mismatches were introduced to the system when a minimum phase behavior was exhibited. Though all the coordination algorithms were able to result in stable

Table 3.6
Performance Indices for the quadruple tank case study (Minimum Phase Configuration)

Control Algorithm	Total SSE	Average # Optimization Calls per MPC
Centralized MPC	1.346	500
Decentralized MPC	1.460	500
Comm. Based MPC	1.437	560
Coop. Based MPC (2 iterations)	1.457	687
Coop. Based MPC (10 iterations)	1.348	938
Price Driven MPC	1.387	668

Table 3.7
Performance Indices for the quadruple tank case study (Non-Minimum Phase Configuration)

Control Algorithm	Total SSE
Centralized MPC	8.328
Decentralized MPC	Unstable
Comm. Based MPC	Unstable
Coop. Based MPC (2 iterations)	9.088
Coop. Based MPC (10 iterations)	8.461
Price Driven MPC	Unstable

closed loop responses, it was observed that the coordination algorithms were most sensitive to gain overestimates as compared to the other mismatches. Once again, price driven coordination was found to be more robust than cooperation based coordination and deviated less from the base values as seen in Table 3.8, Table 3.9, and Table 3.10. In the case of severe overestimates of the process gains, the price driven coordination was seen to significantly outperform cooperation based coordination with a 14.54% lesser deviation.

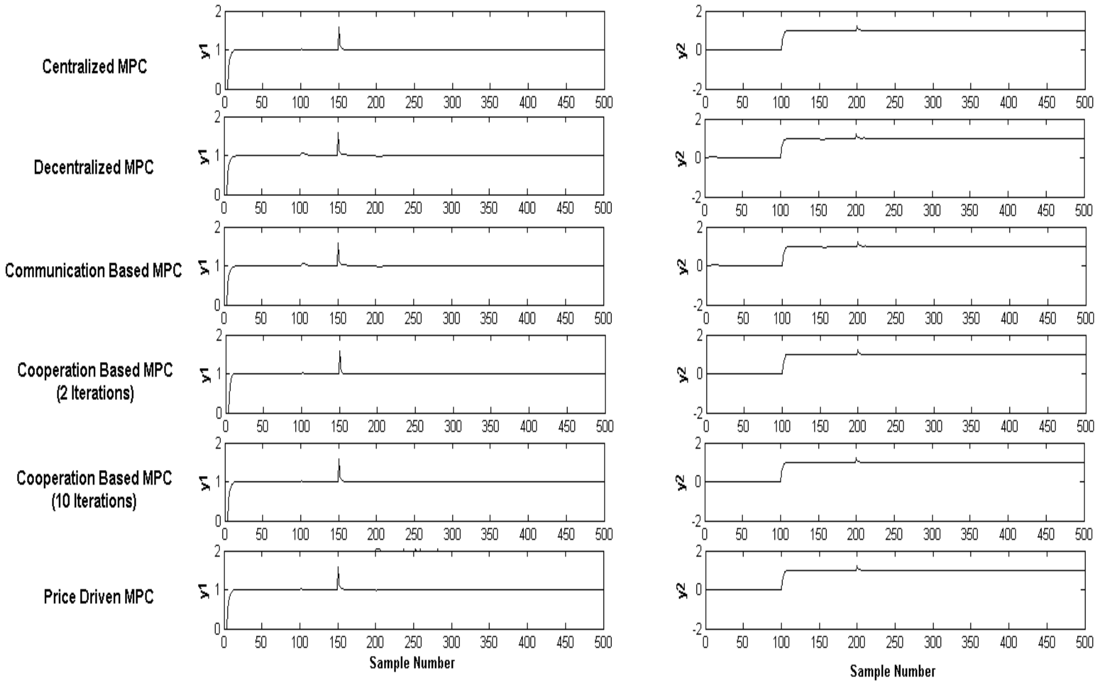

Fig. 3.7. Comparison of the four tank system output variables' response under different control configurations.

Table 3.8
Performance Indices for the quadruple tank case study (Minimum Phase Configuration) in the presence of Model-Plant Mismatch

Gain Mismatch	SSE for Centralized	% Deviation	SSE for Coop. Based MPC (2 iterations)	% Deviation	SSE for Price Driven MPC	% Deviation
+50%	1.401	4.08	1.736	19.15	1.451	4.61
+10%	1.366	1.48	1.491	2.33	1.415	2.02
0% (No Mismatch)	1.346	-	1.457	-	1.387	-
-10%	1.352	0.45	1.472	1.03	1.401	1.01
-50%	1.363	1.26	1.501	3.02	1.426	2.81

Table 3.9
Performance Indices for the quadruple tank case study (Minimum Phase Configuration) in the presence of Model-Plant Mismatch

Dead Time Mismatch	SSE for Centralized	% Deviation	SSE for Coop. Based MPC (2 iterations)	% Deviation	SSE for Price Driven MPC	% Deviation
+50%	1.372	1.93	1.639	12.49	1.436	3.53
+10%	1.353	0.52	1.478	1.44	1.401	1.01
0% (No Mismatch)	1.346	-	1.457	-	1.387	-
-10%	1.349	0.22	1.467	0.69	1.395	0.58
-50%	1.356	0.74	1.491	2.33	1.409	1.59

Table 3.10
Performance Indices for the quadruple tank case study (Minimum Phase Configuration) in the presence of Model-Plant Mismatch

Time Constant Mismatch	SSE for Centralized	% Deviation	SSE for Coop. Based MPC (2 iterations)	% Deviation	SSE for Price Driven MPC	% Deviation
+50%	1.381	2.60	1.651	13.31	1.444	4.11
+10%	1.357	0.82	1.484	1.85	1.407	1.44
0% (No Mismatch)	1.346	-	1.457	-	1.387	-
-10%	1.351	0.37	1.469	0.82	1.398	0.79
-50%	1.360	1.04	1.498	2.81	1.413	1.87

3.4 Conclusions

Coordinating multiple model predictive controllers has been shown to significantly improve the performance of decentralized control strategies, driving them towards the control performance of the centralized controller. Communication of information between controllers was seen to be insufficient to guarantee closed loop stability in the case of the quadruple tank system and even in the shell benchmark problem where it yielded a closed loop stable response; its performance was significantly poorer as compared to the other coordination strategies. To overcome this drawback, objective functions of the local controllers had to be modified to enable the subsystems to cooperate towards a pareto optimal solution. The price driven coordination was also seen to coordinate the local controllers effectively with a significantly lower computational demand.

Cooperation based coordination is the only strategy that asymptotically converges to the centralized controller performance. Also, since at every iteration a closed loop stable and feasible solution is produced, it has the added advantage that it can be stopped at any arbitrary iteration depending on the available computational resources and desired level of performance enhancement. On the other hand, it was also observed that price driven coordination was able to produce the same level of performance as the cooperation based controller at a lower computational effort.

While studying the robustness of the coordination algorithms, price driven coordination was found to be a more robust control strategy as it deviated less from its base performance in the presence of mismatches. As the different algorithms are derived from fundamentally different methodologies, the interaction factors are utilized differently in the various algorithms. This resulted in some algorithms being more sensitive to the accuracy of the interaction models. In the presence of large mismatches where the cooperation based coordination failed, the price driven coordination was still able to come out with a feasible and stable solution.

The system dynamics and level of interaction was also found to have a significant effect on the performance of the coordination algorithms. For the quadruple tank system with non-minimum phase system behavior, only the cooperation based coordination strategy was found to be closed loop stable. This necessitates a good understanding of the system dynamics before choosing an appropriate coordination algorithm, especially for systems with multivariable process zeros, like the quadruple tank system. This will help control practitioners to select the best coordination algorithm based on a priori knowledge of the system behavior and the extent of parametric uncertainties.

The implementation of the C-MPC schemes comes with an increased computational load due to the presence of a communication network and the iterative nature of the algorithms. The size of the communication network increases polynomially with the number of subsystems. However, the dimensionality of the individual optimization problems doesn't change compared to the decentralized control scheme.

The increased computational demands to the communication requirements could impede the scalability of the C-MPC algorithms. In order to overcome this drawback and address the issue of scalability, the next chapter explores a novel methodology that minimizes the communication requirements without impeding the overall performance.

Though coordinating multiple controllers improves the closed loop performances significantly, they come at the cost of increased communications between the controllers and a higher computational effort. Through the analyses of multiple case studies, the advantages and drawbacks of both the coordination algorithms was brought forth. While the price driven coordination algorithm seemed to be more robust in terms of model-plant mismatch, it did not always converge to the performance of the centralized controller and closed loop stability was not guaranteed (unlike the cooperation-based coordination). However, in the next phase of this research we have selected the cooperation-based coordination algorithm and developed strategies to improve its performance. The selection of cooperation-based coordination was mainly motivated by the fact that it was an iterative algorithm that could be stopped at any iteration depending on the available resources making it practically very convenient. Also, the very nature of the formulation made it convenient for the next phase of studies on minimum information exchange.

Though coordinating multiple controllers improves the closed loop performances significantly, they come at the cost of increased communications between the controllers and a higher computational effort due to the communication exchange between the controllers. Through the analyses of multiple case studies, the advantages and drawbacks of both the coordination algorithms was brought forth. While the price driven coordination algorithm seemed to be more robust in terms of model-plant mismatch, it had issues with the convergence to the centralized performance and closed loop stability both of which are not guaranteed (unlike the cooperation-based coordination). However, in the next phase of this research we have selected the cooperation-based coordination algorithm and developed strategies to improve its performance. The selection of cooperation-based coordination was mainly motivated by the fact that it was an iterative algorithm that could be stopped at any iteration depending on the available resources making it practically very convenient. Also, the very nature of the formulation made it convenient for the next phase of studies on minimum information exchange.

Chapter 4

MINIMUM INFORMATION EXCHANGE BASED C-MPC ARCHITECTURES

4.1 Introduction

Most formulations of coordinated and distributed control strategies in literature are hinged on the assumption that every controller communicates with every other controller. This assumption creates a tremendous load on the communication network, resulting in an overly complex coordination algorithm. Methods to reduce the communication load through algorithms that permit only partial cooperation is the direction in which current research is progressing and a few methods that try to tackle this problem has been presented in recent literature (Schuler et al. (2011)). In Schuler's work, the authors designed decentralized controllers that utilize both the output of its own subsystem as well as selected outputs of other subsystems. They then addressed the problem of minimizing the number of additional outputs utilized by each controller while guaranteeing a stable performance. In our work, a robust methodology that could utilize most existing coordinated MPC (C-MPC) schemes to identify a partial communication architecture that does not significantly affect the overall optimality of the system is developed. We have developed and analyzed a simulation-based optimization (Law & McComas (2000)) method to reduce the communication load without compromising the closed-loop stability, or the overall system performance significantly. A framework to achieve the same is described in the next section.

4.2 Minimum Information Exchange Based Coordination

The problem of simultaneously designing both the controller topology and the controller itself has been introduced very recently (Negenborn & Maestre (2014)) and is one of the main contributions of this research. In our work, we have first designed the C-MPC control strategy with complete information exchange (as described in Chapter 3) and then we have optimized the communication topology within the C-MPC architecture. We now formulate the problem of minimizing the information exchange and optimizing the topology of the C-MPC architecture. Mathematically this problem translates into maximizing the sparsity of $\tilde{G}_p$ (defined in eq. 3.2) which in turn increases the degree of decentralization which is quantified through an Interaction Matrix.

The Interaction Matrix is defined as,

$$IM = \begin{bmatrix} 1 & im_{12} & . & . & im_{1M} \\ im_{21} & 1 & . & . & im_{2M} \\ . & . & . & . & . \\ . & . & . & . & . \\ im_{M1} & im_{M2} & . & . & 1 \end{bmatrix} \tag{4.1}$$

where

$$im_{ij} = 0, \text{ if interaction model } G_{ij} \text{ is ignored}$$

$$im_{ij} = 1, \text{ if interaction model } G_{ij} \text{ is utilized}$$

and the interaction index (II) of the control topology is defined as:

$$II = \sum_{i=1}^{M} \sum_{j=1}^{M} im_{ij} \tag{4.2}$$

It is desired to minimize the number of interaction models used in the control architecture. However, as the number of utilized interaction models are reduced, the system performance also deteriorates due to the reduction in information, which is undesired, and hence a multi-objective optimization (MOO) problem is formulated. In this case we have two conflicting objectives, the number of interaction models (II) and the performance deterioration of the system (quantified through the SSE).

Traditionally, multi-objective optimization problems are solved using the min-max formulation, method of distance functions, or the method of weighted objectives (Marler & Arora (2004)) where the multiple objectives are converted into a single objective. The greatest drawback of these methods is the resulting single solution rather than a pareto optimal solution set. Also, the conversion of multiple objectives into a single objectives depends on an a priori requirement of system knowledge. Moreover, these methods involve weighing of objectives, and the tuning of these weights plays a significant role in the overall optimality of the solutions. These short-comings render the single-objective formulation based methods inadequate and and of little practical significance. In order to provide a more pragmatic set of solutions that enable the decision maker to choose the most appropriate decision based on current requirements, algorithms that explicitly handle multiple objectives are available - they yield a set of solutions known as pareto optimal solutions (Rangaiah (2008)). Each of these solutions in the pareto optimal set is better than every other solution in the search space when all the objectives are considered together. Many methods have been developed to find Pareto optimal solutions to MOO problems such as the weighted sum method, ϵ-constraint method, evolutionary algorithms (Tamaki et al. (1996)), etc. In this work, we have utilized a multi-objective evolutionary algorithm in the form of the non-dominated sorting genetic algorithm (NSGA-II) implemented in MATLAB. As described in Deb et al. (2000) this particular algorithm performs better than other MOO algorithms (Pareto-archived evolution strategy (PAES) and strength Pareto evolutionary algorithm (SPEA)), in terms of elitism and computational complexity.

The schematic representation of non-dominated sorting genetic algorithm is shown in Fig. 4.1 and the algorithm is set up as follows. The first step is to define the population size and the stopping criteria (in this case the number of generations was constrained). Next, within the constraints of the decision variables, a random initial population is defined. The initialized population is sorted into different fronts, based on the non-domination criteria. From the initial population, parents are selected based on two metrics namely rank and crowding distance. The members of the first front belong completely to the non-dominated set while the second front members are dominated only by the first front and so on. Each individual of the population is assigned a rank (fitness) based on the their presence in a particular front. Crowding distance is a metric that measures the closeness of the individuals to their neighbors and a larger crowding distance is preferred to ensure diversity within the population. Individuals are selected as parents based on the rank value and crowding distance. The parent population then undergoes genetic operations such as crossover and mutation to generate the next generation of the population known as children. The children population is then combined with the current parent population in a step called recombination. These steps are repeated iteratively till the stopping criteria are achieved. Elitism of the algorithm is assured, since the best individuals from both the previous and current population are utilized. The parameters involved in setting up the NSGA-II algorithm are the number of generations and the probabilities for the crossover and mutation processes. One of the challenges associated with this algorithm is the decision of the initial population size and maximum permissible number of iterations. Though a larger population and number of iterations are preferred, they significantly increase the computational cost and need to be limited yet sufficient. However, the optimization problem described in this work is a design problem and is performed to select the optimal communication topology that needs to be implemented within the C-MPC framework. This permits a large number of generations to be utilized in order to allow the GA algorithm to converge. In this work, a modified version of the program developed at the Illinois Genetic Algorithms Laboratory (Sastry (2007)) was used and the parameters used in the setting up of the NSGA-II algorithm are specified for the various case studies in Table 4.1.

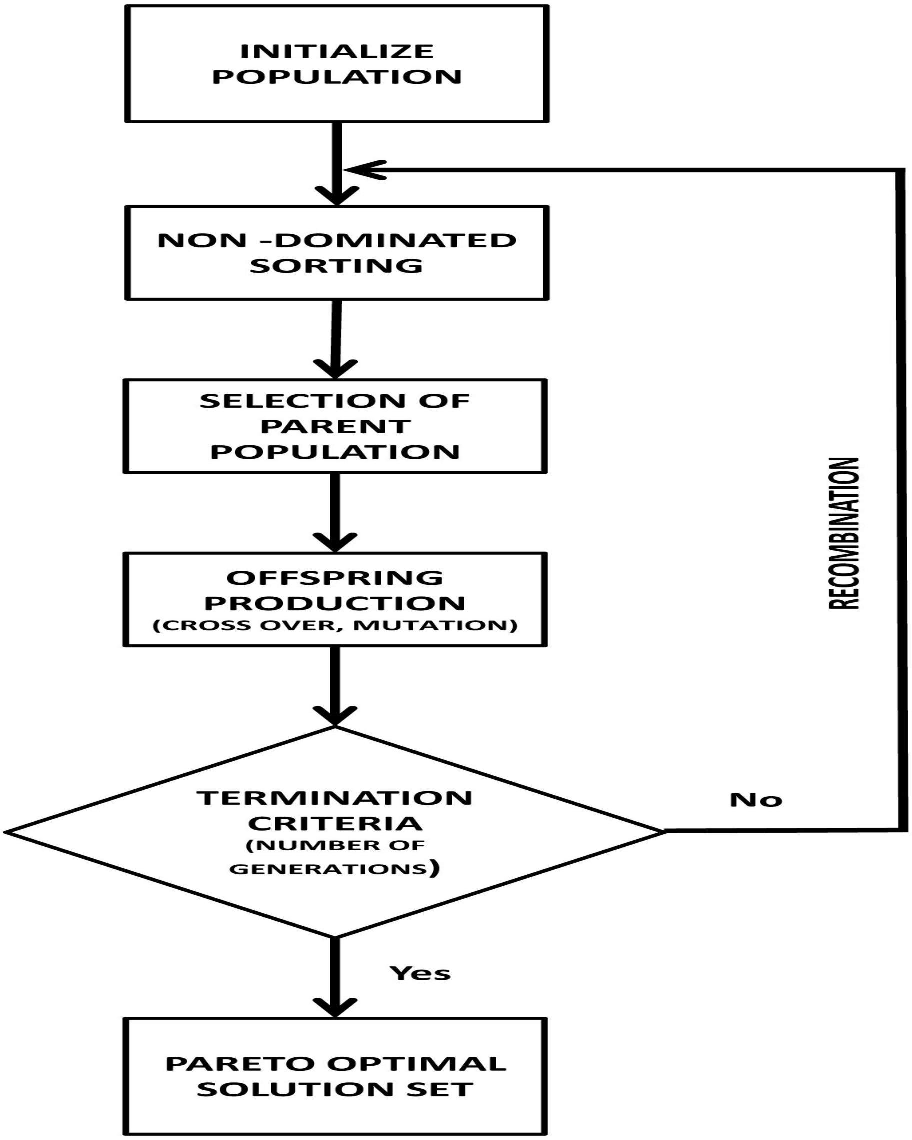

Fig. 4.1. A schema of the implemented NSGA method

The GA optimization is computationally intensive and the computational time required to optimize the control architecture increases significantly with the number of subsystems. The number of interactions increases polynomially ($O(n^2)$) with the number of subsystems and the number of possible communication topologies increases exponentially ($O(2^{n^2}$) with the number of subsystems. This indicates that even a moderately large system comprising of 5 subsystems could result in a search

Table 4.1
NSGA Parameters

Fixed Parameters	
Objective 1	Minimize SSE (eq. 11)
Objective 2	Minimize II (eq. 13)
Decision Variables	Binary Variables
Replacement Proportion	0.9
Selection Method	Roulette Wheel
Crossover Method	One Point Crossover
Crossover Probability	0.9
Mutation Method	Selective Mutation
Mutation Probability	0.1
Stopping Criteria	Maximum Number of Generations
Variable Parameters	
Population Size	Case Study 1: 36
	Case Study 2: 36
	Case Study 3: 200
Maximum Number of Generations	Case Study 1: 200
	Case Study 2: 200
	Case Study 3: 500

space of over 1 million possible communication topologies (as seen in Fig. 4.2 and Fig. 4.3). This necessitates the need to improve the convergence rate of the GA algorithm. One way in which this can be achieved, is by reducing the search space and any method that reduces the search space significantly would greatly benefit practical applications of this methodology. In order to decrease the computational requirements we investigated the utility of many well known interaction indices (Grosdidier & Morari (1986), Lee et al. (1998), Salgado & Conley (2004), etc.) as an *a priori* qualitative interaction quantifier that can be utilized to reduce the GA search space by identifying the most significant interactions and ensuring that these interactions are always accounted for.

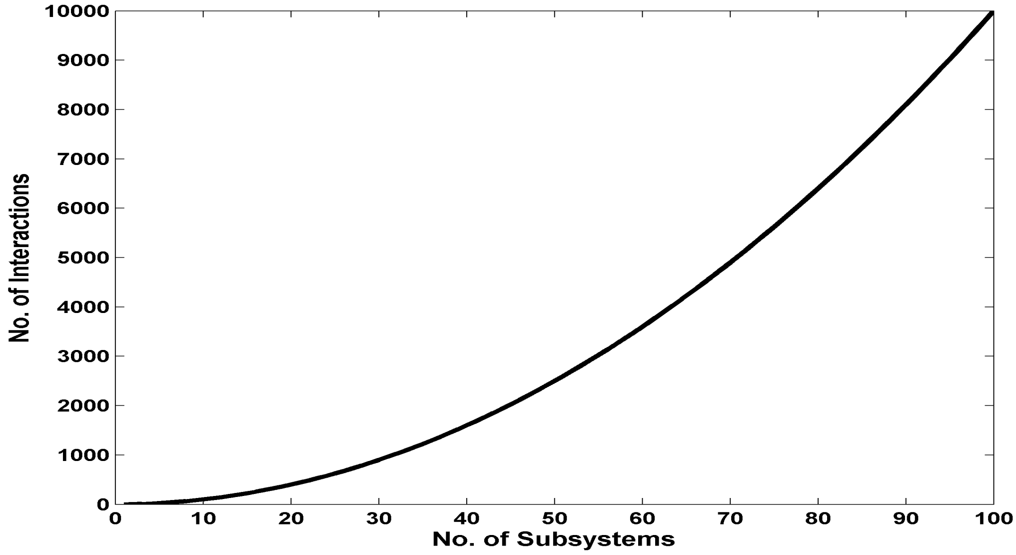

Fig. 4.2. Relation between number of subsystems and the corresponding number of interactions

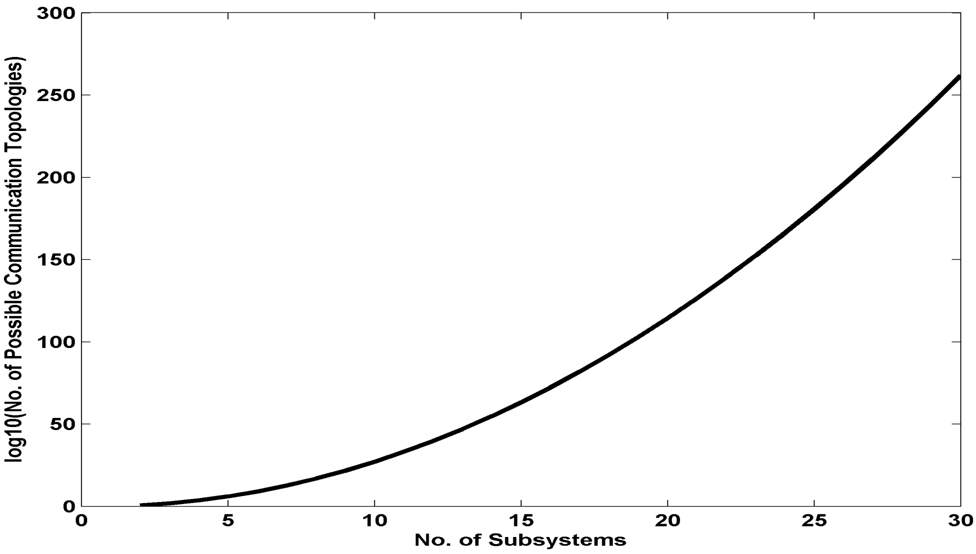

Fig. 4.3. Relation between the number of subsystems and the possible number of communication topologies

Various methods have been proposed in literature to quantify the interaction effects for loop pairing to design the control loop configuration. Beginning with the relative gain array (RGA) which utilizes only the steady state gain, researchers have proposed various variations like dynamic relative gain array (DRGA, McAvoy (1983)), normalized relative gain array (NRGA, Fatehi (2011)), effective relative gain array (ERGA, Monshizadeh-Naini et al. (2009)), etc. to overcome its drawbacks. One such criterion is the RNGA, which utilizes both the steady state as well as dynamic information of a process to achieve a more comprehensive quantification of the interactions in a system. In this method, instead of utilizing only the steady state gain matrix, the entire transfer function model of the process is utilized to ensure that the process dynamics are well captured.

As defined by He et al. (2009) , The normalized gain for a transfer function is given by,

$$k_{N,ij} = \frac{G_{ij}(j0)}{\tau_{ar,ij}} \tag{4.3}$$

where, $\tau_{ar,ij}$ is the average residence time of the system. The steady state gain captures the sensitivity of the controlled variable on the manipulated variable and the average residence time accounts for the response speed of the controlled variable to changes in the manipulated variable. Hence, a large normalized gain would mean either a large steady state gain or a low residence time implying that the controlled variable is highly sensitive to the manipulated variable. Now, the normalized gain matrix of the system is given by,

$$K_N = G(j0) \odot \Gamma_{ar} \tag{4.4}$$

The larger the value of an element in the normalized gain matrix, the larger will the dominance of that particular control pairing. The relative normalized gain is calculated for all input-output combinations and the RNGA is given by,

$$\Phi = K_N \otimes K_N^{-T} \tag{4.5}$$

where the value of ϕ_{ij} is a measure of the effective interaction. A large positive ϕ_{ij} indicates that the manipulated variable (u_j) has a significant effect on the control variable (y_i) and its response speed, which signifies a strong interaction. Through the analyses of multiple case studies, it was seen that the values in the RNGA matrix had a strong correlation with the interaction selection optimized by the GA algorithm. This strong correlation lead to the possibility of incorporating the RNGA results into the GA optimizer in order to reduce the search space. In this work, to incorporate the RNGA results with the GA optimizer, positive off-diagonal RNGA values were deemed to significantly affect the overall C-MPC performance and the corresponding interaction models were fixed $(im_{ij} = 1)$ and not included in the decision variable set while optimizing the controller topology. The GA-RNGA based communication topology optimizer was then evaluated on a few independent case studies.

4.3 Case Studies

In order to analyze and evaluate the performance of the C-MPC architecture with minimum information exchange the results from three popular benchmark systems which exemplify the nature of the novel control scheme and elucidates its efficacy, are presented here. A tuning strategy derived by Shridhar & Cooper (1997) was used to tune the individual multivariable MPCs. Model based controllers based on transfer function models were derived and implemented in MATLAB version 7.11.0.584. In order to assess the robustness of the developed control algorithm, set point changes as well as step disturbances were introduced to all the subsystems at different sampling instants.

4.3.1 Shell Benchmark Problem

The Shell benchmark problem described in Section 3.3.1 is once again used as a test case to study the efficiency of the minimum information exchange based C-MPC scheme.

The interactions are quantified using the relative normalized gain array (RNGA). The RNGA for the system is $\begin{bmatrix} 2.3324 & -1.6519 & 0.3194 \\ -0.9069 & 2.7975 & -0.8905 \\ -0.4254 & -0.1456 & 1.5711 \end{bmatrix}$

The presence of significant off-diagonal terms indicates the existence of subsystem interactions that exist in the system. The simulation results (Fig. 4.4), indicated that the effect of these interactions were strong and though the decentralized control strategy (0 interactions) yielded a closed loop stable solution, its performance was significantly degraded as compared to the centralized controller performance (6 interactions). In order to assess the effectiveness of the C-MPC control architecture, the GA-RNGA algorithm was implemented. The most significant interaction model as indicated by the RNGA, was im_{13} with a $\phi_{13} = 0.3194$ which is also the only positive off-diagonal RNGA value. Since this was the single most significant interaction model, its value was fixed as 1 in the interaction matrix and only the remaining 5 decision variables (interaction models) were optimized while configuring the communication topologies.

The results as seen in Fig. 4.4, highlight the utility of the GA-RNGA optimization algorithm in selecting communication architectures with varying topologies of different complexities. While the top panel of the figure depicts the performance of the controller while utilizing different number of interaction models, the lower panel shows the corresponding optimal interaction models that were selected to achieve the depicted performance. It is seen that including a single interaction model (im_{13}), if selected optimally can improve the decentralized performance by nearly 50% as seen in Table 4.2. Also, it is seen that, by increasing the number of interactions, the performance improves (SSE decreases) and asymptotically converges to the performance of a centralized controller. Through utilizing the GA-RNGA optimization algorithm, the importance of the individual interactions as well as the selection of

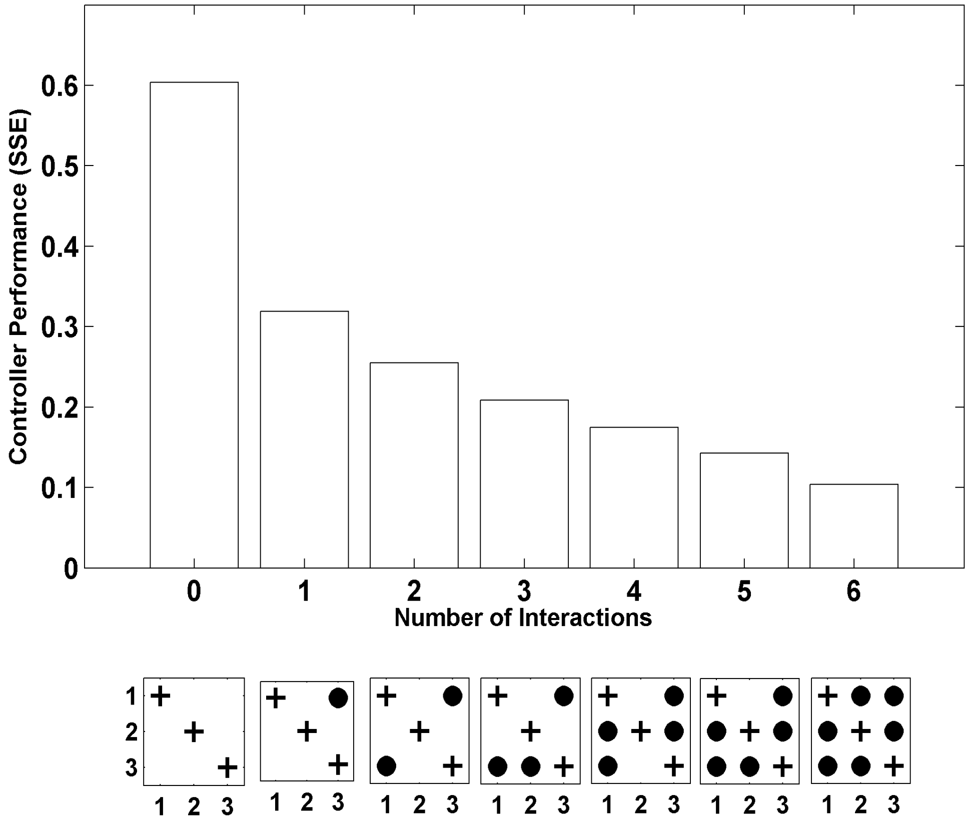

Fig. 4.4. Performance comparison of the shell benchmark problem for various optimal interaction topologies ($im_{31} = 1$)

an optimal control topology with limited communication (as desired by plant operators) can be achieved. When more interaction models are included in the control topology, the required computational time would also increases. The increase in time can be attributed to the increase in communication and the exchange of information between a larger number of controllers. However, this would provide the plant operators with a trade-off option between desired performance improvement and available computational resources. For example, if the time constraints permit only the selection of 3 then the interaction models im_{13}, im_{31} and im_{32} need to selected and a performance enhancement of 65.6% can be achieved. Conversely, if a performance enhancement of 50% is sufficient, only 2 interaction models need to be utilized.

Table 4.2
Performance comparison of the various optimal control topologies for the shell benchmark problem

No. of Interactions	**SSE with respect to Decentralized MPC**
Decentralized MPC	1.000
1	0.528
2	0.421
3	0.344
4	0.288
5	0.235
6	0.171
Centralized MPC	0.161

4.3.2 Distillation Column Control

Ogunnaike and Ray (Ogunnaike et al. (1983)) developed a multi-product pilot plant distillation column (Fig. 4.5) to evaluate the efficiency of their multivariable control strategy. This has since become a benchmark test case to evaluate the efficiency of new control strategies. The multiproduct ethanol-water distillation column is a multivariable system having multiple time delays making it hard to control. The controlled variables of the binary ethanol-water system are the overhead ethanol mole fraction, side stream ethanol mole fraction and temperature of the 19^{th} tray. The manipulated variables for this system, are the reflux flow rate, side stream product flow rate and the reboiler stream pressure. The tuned parameters were as follows: prediction horizon = 60, control horizon = 5 and move suppression vector = [1 10 10]. The distillation column was modeled as the following transfer function, The model of the process is: $y = G(s)u + G_d(s)d$ with the transfer function matrices:

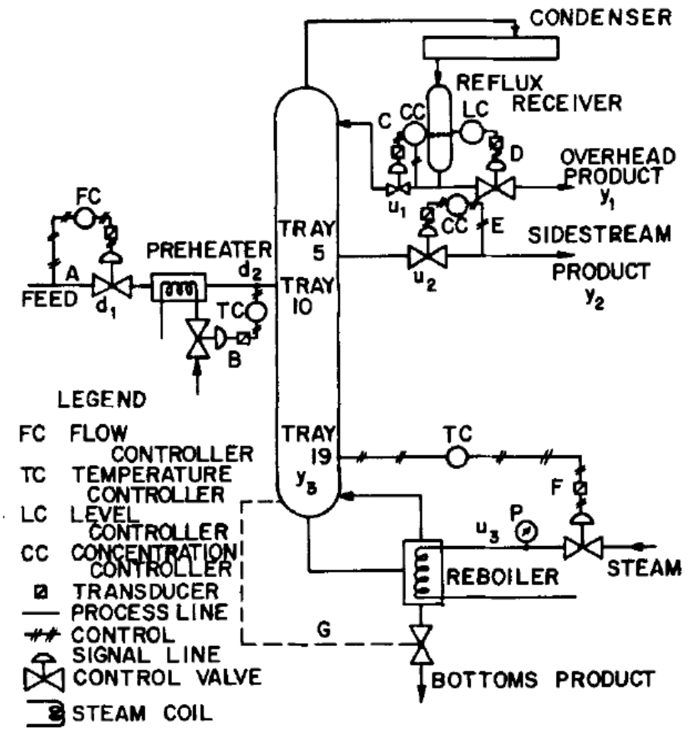

Fig. 4.5. Distillation column control schematic (Adapted from Ogunnaike et al. (1983))

$$G(s) = \begin{bmatrix} \frac{0.66e^{-2.6s}}{6.7s+1} & \frac{-0.61e^{-3.5s}}{8.64s+1} & \frac{-0.0049e^{-1.0s}}{9.06s+1} \\ \frac{1.11e^{-6.5s}}{3.25s+1} & \frac{-2.36e^{-3s}}{5s+1} & \frac{-0.01e^{-1.2s}}{7.09s+1} \\ \frac{-34.68e^{-9.2s}}{8.15s+1} & \frac{46.2e^{-9.4s}}{10.9s+1} & \frac{0.87(11.61s+1)e^{-1s}}{(3.89s+1)(18.8s+1)} \end{bmatrix} \text{ and } G_d(s) = \begin{bmatrix} \frac{0.14e^{-0.2s}}{6.2s+1} \\ \frac{0.53e^{-0.5s}}{6.9s+1} \\ \frac{-11.54e^{-0.6s}}{7.01s+1} \end{bmatrix}$$

The constraints include,

$|y_i| \le 10$, $|u_i| \le 10$, $|\Delta u_i| \le 5$ for $i = 1, 2, 3$

The interactions are quantified using the relative normalized gain array (RNGA).

The RNGA for the system is $\begin{bmatrix} 1.4827 & -0.3485 & -0.1342 \\ -0.3443 & 1.407 & -0.0614 \\ -0.1384 & -0.0572 & 1.1956 \end{bmatrix}$

The presence of significant off-diagonal terms indicated the severe interaction that exists in the system. Also, through simulations it was seen that the difference in performance between a centralized and decentralized control architecture was quite high (i.e.) a decentralized control architecture while closed loop stable was performing significantly worse than a centralized controller. This performance gap motivates the requirement of a C-MPC control strategy that is able to identify the most significant interactions and develop a control topology that utilizes only a few of the interactions while substantially driving the performance towards that of a centralized controller. In order to assess the effectiveness of the C-MPC control architecture with varying topologies of different complexities, the GA-RNGA optimization algorithm was implemented. However, in this case, while the interactions were strong, there were no positive RNGA off-diagonal elements and hence the GA-RNGA algorithm was implemented without any textita priori modifications and the results are seen in Fig. 4.6. Again, it is clearly evident that, by increasing the number of interactions, the performance improves (SSE decreases) and converges to the performance of a monolithic centralized controller.

Through utilizing the GA-RNGA optimization algorithm, the importance of the individual interactions as well as the selection of an optimal control topology with limited communication can be achieved. It was seen that im_{31}, im_{32} and im_{21} are

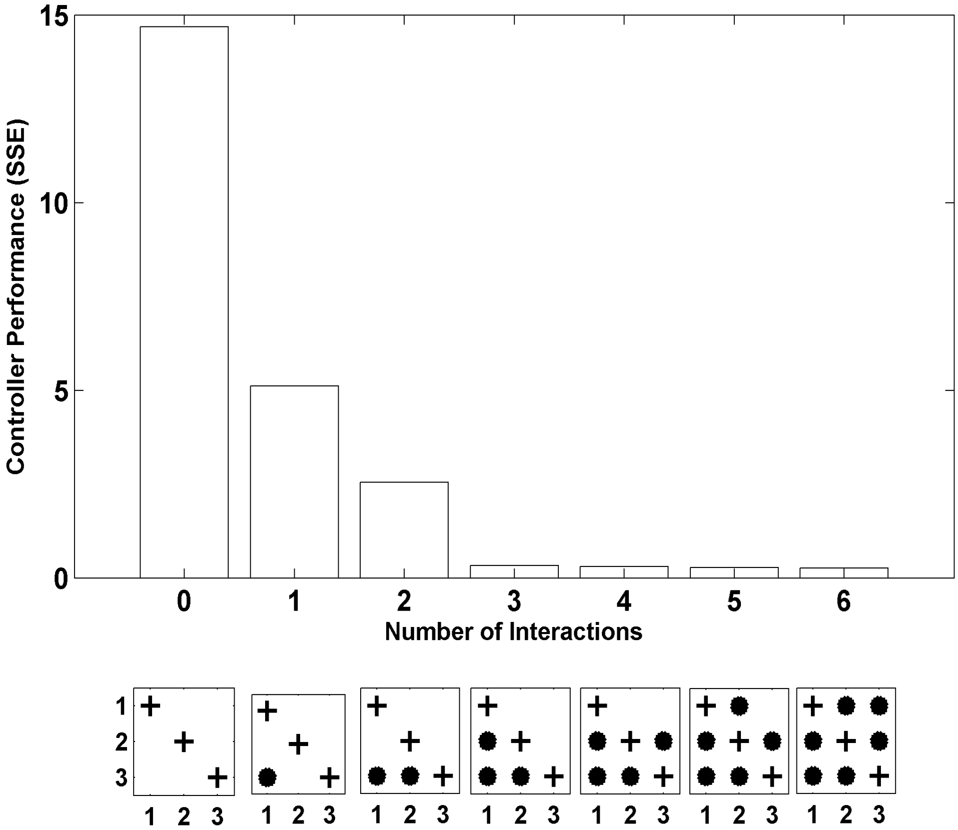

Fig. 4.6. Performance comparison of the distillation column case study for various optimal interaction topologies

the most significant interactions and need to utilized to improve the performance significantly. As shown in Table 4.3, selecting three interactions optimally can improve the decentralized performance by nearly 98%. This indicates that the three most significant interactions if selected optimally can result in near global optima and the computational requirements of utilizing 3 interactions are definitely less than the complete communication architecture where all 6 interactions are utilized.

Table 4.3
Performance comparison of the various optimal control topologies for the distillation column case study

No. of Interactions	**SSE with respect to Decentralized MPC**
Decentralized MPC	1.000
1	0.349
2	0.174
3	0.023
4	0.021
5	0.019
6	0.019
Centralized MPC	0.018

4.3.3 Complex Sidestream Column/Stripper Distillation Control

Alatiqi (Alatiqi & Luyben (1986)) studied the dynamics and control of a complex, multivariable sidestream column/stripper distillation configuration with multiple feeds and products. These systems are highly interacting and quite hard to control. The system design is seen in Fig. 4.7, and the process modeled was the separation of benzene and toluene from a ternary mixture of benzene, toluene and xylene. The controlled variables of this system are the benzene composition in the distillate, toluene composition in the sidestream, bottom composition of xylene and the temperature difference between the trays above and below the sidedraw tray. In order to ensure product purity and minimize energy consumption, the manipulated variables selected were the liquid side draw rate from the main column to the stripper, main column reboiler heat duty, stripper reboiler heat duty and the reflux flow rate. The tuned parameters were as follows: prediction horizon = 37, control horizon = 6 and move suppression vector = [15 15 20 25]. In our work we have modeled this system and evaluated the efficiency of the coordinated control architecture on this popular 4x4 multivariable benchmark system. The 4x4 system significantly increases the complexity over the previous 3x3 case studies by increasing the possible interaction topologies (search space), which is related exponentially to the number of subsystems as shown previously.

The model of the process is: $y = G(s)u + G_d(s)d$ with the transfer function matrices:

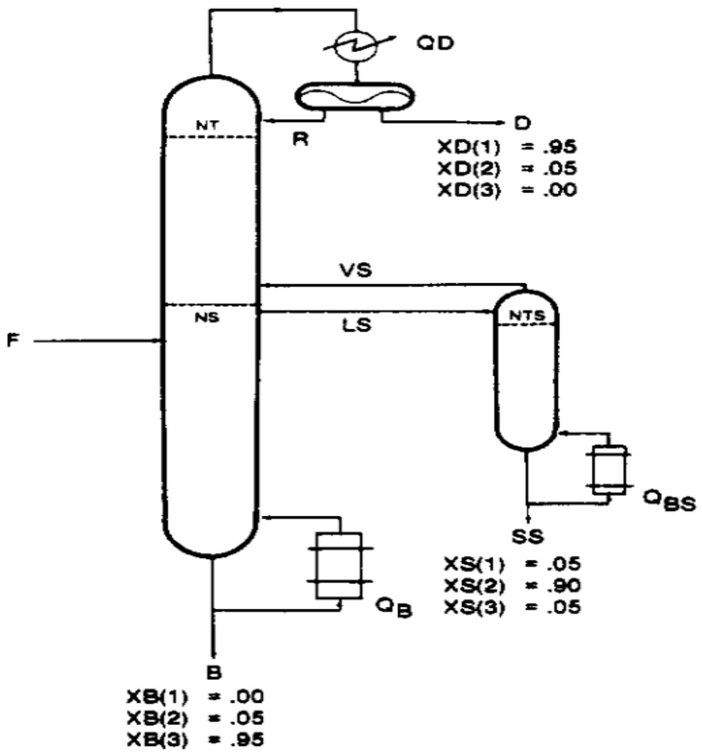

Fig. 4.7. Complex Sidestream Column/Stripper Distillation Control Schematic (Adapted from Alatiqi & Luyben (1985))

$$G(s) = \begin{bmatrix} \frac{4.09e^{-1.3s}}{(33s+1)(8.3s+1)} & \frac{-6.36e^{-0.2s}}{(31.6s+1)(20s+1)} & \frac{-0.25e^{-0.4s}}{21s+1} & \frac{-0.49e^{-5s}}{(22s+1)^2} \\ \frac{-4.17e^{-4s}}{45s+1} & \frac{6.93e^{-1.01s}}{44.6s+1} & \frac{-0.05e^{-5s}}{(34.5s+1)^2} & \frac{1.53e^{-2.8s}}{48s+1} \\ \frac{-1.73e^{-17s}}{(13s+1)^2} & \frac{5.11e^{-11s}}{(13.3s+1)^2} & \frac{4.61e^{-1.02s}}{18.5s+1} & \frac{-5.48e^{-0.5s}}{15s+1} \\ \frac{-11.18e^{-2.6s}}{(43s+1)(6.5s+1)} & \frac{14.04e^{-0.02s}}{(45s+1)(10s+1)} & \frac{-0.1e^{-0.05s}}{(31.6s+1)(5s+1)} & \frac{-4.49e^{-0.6s}}{(48s+1)(6.3s+1)} \end{bmatrix}$$

and $G_d(s) = \begin{bmatrix} \frac{1.44e^{-27s}}{40s+1} \\ \frac{1.83e^{-15s}}{20s+1} \\ \frac{1.26}{32s+1} \\ \frac{2}{20s+1} \end{bmatrix}$

The interactions are quantified using the relative normalized gain array (RNGA).

The RNGA for the system is $\begin{bmatrix} 1.8033 & -0.4423 & -0.1774 & -0.1836 \\ -1.0320 & 2.2582 & 0.0291 & -0.2553 \\ -0.0212 & 0.0246 & 1.2330 & -0.2364 \\ 0.2498 & -0.8405 & -0.0847 & 1.6754 \end{bmatrix}$

The presence of significant off-diagonal terms indicates the strong interactions exist in the system. The GA-RNGA optimization algorithm was implemented and the effectiveness of the C-MPC control architecture with varying topologies of different complexities was analyzed. While there were three off-diagonal RNGA with positive values, im_{41} was significantly larger than im_{32} and im_{23}. In Fig. 4.8, the results from setting im_{41}=1 are shown. Once again the performance improvement through utilizing more interaction models and the convergence to the centralized controller performance are seen in Table 4.4. Also, the computation time-performance improvement trade-off indicated that selecting 3 interactions were sufficient to significantly improve the performance (over 50%).

The results from fixing all three interactions with a positive RNGA value (im_{41}, im_{32} and im_{23}) 1 in the IM matrix and optimizing only the remaining 9 decision variables are shown in Fig. 4.9. The difference between including and not including

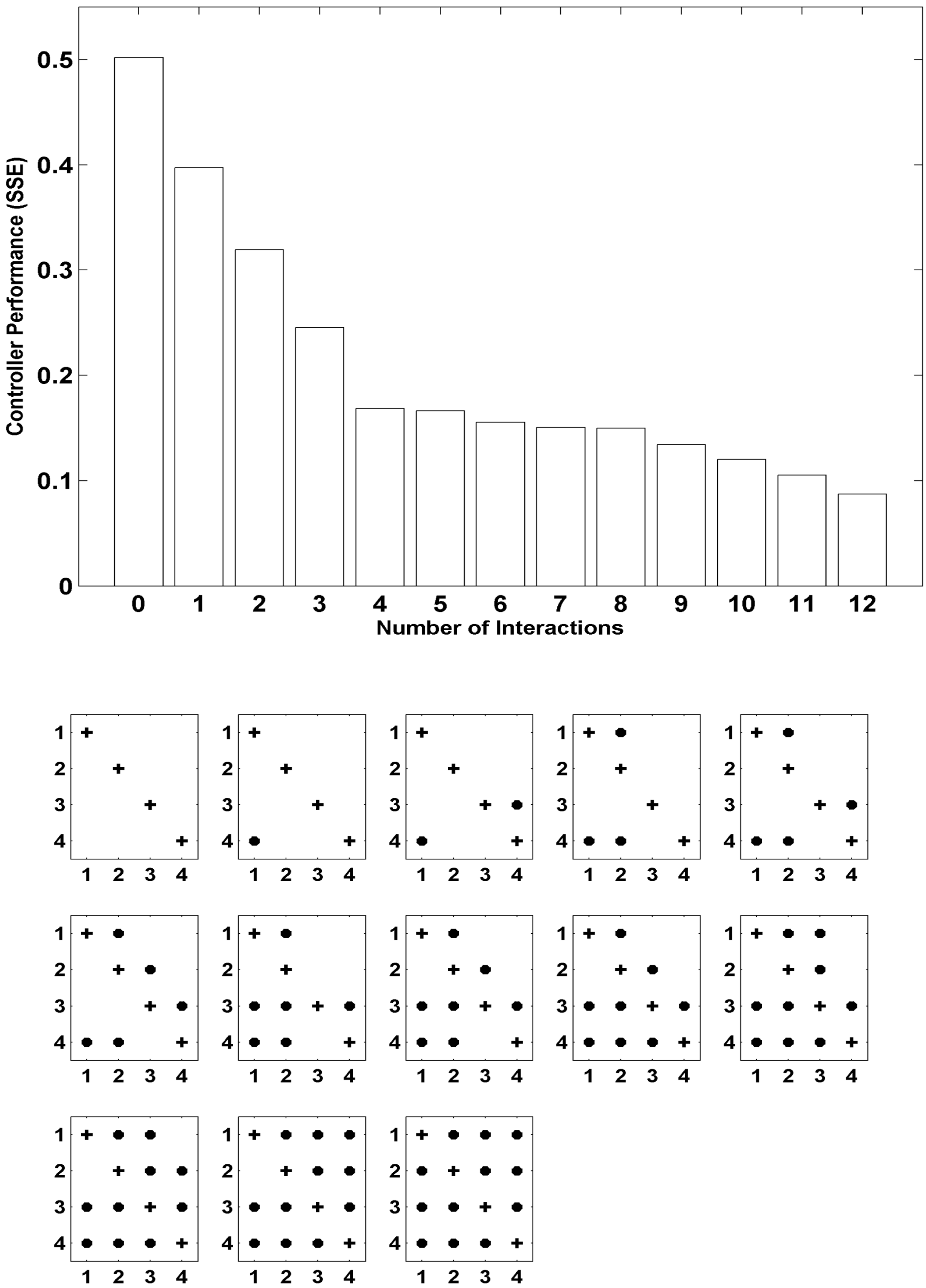

Fig. 4.8. Performance comparison of the complex sidestream stripper case study for various optimal interaction topologies ($im_{41} = 1$)

the models with small RNGA values are seen in the controller topologies with 3, 4, 5 and 6 interactions. The controller topologies with less than 3 or more than 6 interactions are selected identically by both optimization schemes. As mentioned previously, im_{32} and im_{23} are not significantly strong interactions and fixing them as 1 in the interaction matrix results in a few suboptimal solutions. However, even in the four cases where the solution differed (from the simulation with only $im_{41} = 1$), the solution set was better than the decentralized control architecture, resulted in a stable response and was able to converge to the centralized controller performance. This indicated that it is still possible to improve overall controller performance significantly through utilizing the RNGA as a interaction quantifier and lowering the decision variable set from 12 to 9 which reduced the GA search space by one order of magnitude as seen in Fig. 4.3.

From the tabulated computational times per controller (Table 4.4), it is seen that a 50-60% performance improvement is possible by selecting 3 or 4 interactions optimally without significantly increasing the computational costs. For greater performance improvement, if more computational resources is available, 9 or 10 interactions can be selected to enhance the performance by nearly 75%.

4.4 Communication Disruption

The aim of designing the minimum information exchange based coordinated MPC scheme was to try and achieve a performance as close to the centralized MPC performance with minimum communication between the controllers. Such a strategy

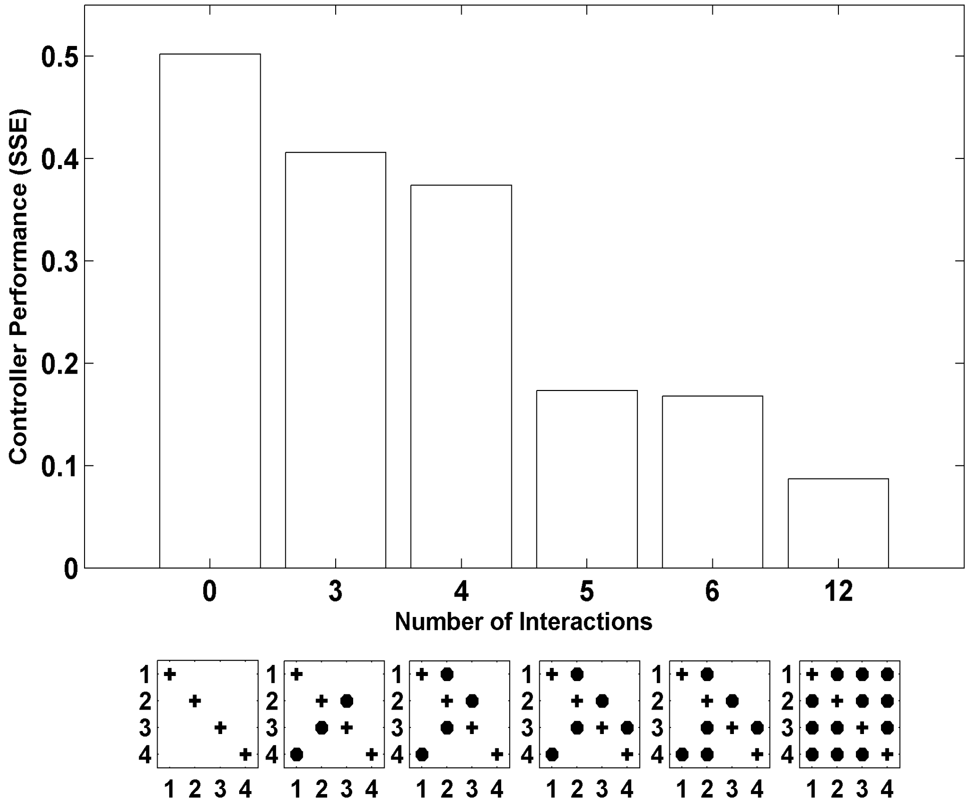

Fig. 4.9. Performance comparison of the complex sidestream stripper case study for various optimal interaction topologies ($im_{41} = im_{32} = im_{23} = 1$)

not only reduces the required computational effort but also increases the robustness of the system. One of the common problems that most large-scale systems encounter is communication disruptions where data being transmitted between controllers is either delayed, corrupted or lost. In the C-MPC architecture described in this work, the subsystems exchange information such as states, predicted output trajectory and calculated control moves. These information are paramount to coordinating the controllers and disruptions or corruption in data could result in the individual controllers destabilizing the entire system. In order to avoid this, one possible fail-

Table 4.4
Performance comparison of the various optimal control topologies for the complex sidestream stripper case study

No. of Interactions	**SSE with respect to Decentralized MPC**
Decentralized MPC	1.000
1	0.791
2	0.635
3	0.488
4	0.337
5	0.331
6	0.309
7	0.299
8	0.299
9	0.267
10	0.239
11	0.209
12	0.174
Centralized MPC	0.110

safe strategy is to revert back to the original decentralized control scheme that does not involve the communication and exchange of information. There are studies in literature that develop strategies to tackle communication disruption in networks from an information technology perspective (Imer et al. (2006) and Casavola et al. (2006)). In this section, we have explored the potential of utilizing the results of the GA-RNGA based communication topology optimizer to provide backup communication strategies in the event of communication disruptions.

In systems where coordinated MPC schemes are implemented based on a full communication topology, the GA-RNGA based minimum information exchange strategy can help reduce the amount of communication by selecting an optimal communication topology. The system can now be run with only a few selected subsystems exchanging information while the remaining communication links can be taken offline. Since a genetic algorithm based optimizer was utilized, a set of pareto optimal solutions are obtained. Also, the genetic algorithm is an iterative procedure, with the solutions improving as each generation evolves. This leads to a set of progressively improving pareto fronts being available for every generation from start till termination. This information can now be used to select alternate communication topologies in the event of communication disruptions. The application of the GA-RNGA based optimization results to tackle communication disruptions is illustrated through an example.

In case study 4.3.3, there were 12 interaction models and an optimal pareto front for selecting communication topologies for varying complexities was provided in Fig. 4.8 and Fig. 4.9. Assuming that the communication topology involving 6 interaction models was selected from Fig. 4.8, based on desired performance improvement and permissible computational effort. The 6 selected interaction models are im_{12}, im_{31}, im_{32}, im_{34}, im_{41} and im_{42} and the information exchange scheme is presented in Table 4.5. As seen in the table, the information regarding the calculated control trajectories are exchanged between a few of the susbystems only. In the event of a communication disruption where subsystem 2 is not being able to transmit information to subsystem 3, one option would be for the coordinator to only coordinate the subsystems with the 5 remaining interaction models. However, the studies in the previous section showed that while using selecting 5 interactions, if the 5 interactions are not chosen optimally, the performance could deteriorate significantly. In order to identify an alternate communication topology with a performance equivalent to the existing control architecture, the catalog of pareto fronts generated by the GA optimizer can be searched with constraints on the availability of information to ensure that the disrupted communication link is explicitly accounted for. An additional constraint can be employed to ensure that utilization of existing communication links is maximized. This is quantified through the similarity index that calculates the percentage of interaction models common between the communication topologies before and after disruption of communication. In this case, we ensured that im_{32} was not utilized and also that the similarity index was at least 60%. The possible alternate communication topologies that the search came up with are shown in Fig. 4.10. Panel (a) depicts the existing system before communication disruption; panels (b) and (c) depict communication topologies utilizing only 5 interaction models and panels (d) and (e) depict alternate communication topologies utilizing 6 interaction models. The performance of the selected alternate communication topologies are shown in table 4.6. It is seen that it is possible to select alternate communication topologies without requiring to revert to the decentralized control architecture. Also, most of the subsystem communications present before the disruption are retained, making quite easy to switch to an alternate communication topology.

Table 4.5
Information exchange scheme for 6 interactions topology of the complex sidestream stripper case study

Information Exchange	
Information From	**Information To**
Subsystem 2	Subsystem 1
Subsystem 1	Subsystem 3
Subsystem 2	Subsystem 3
Subsystem 4	Subsystem 3
Subsystem 1	Subsystem 4
Subsystem 2	Subsystem 4

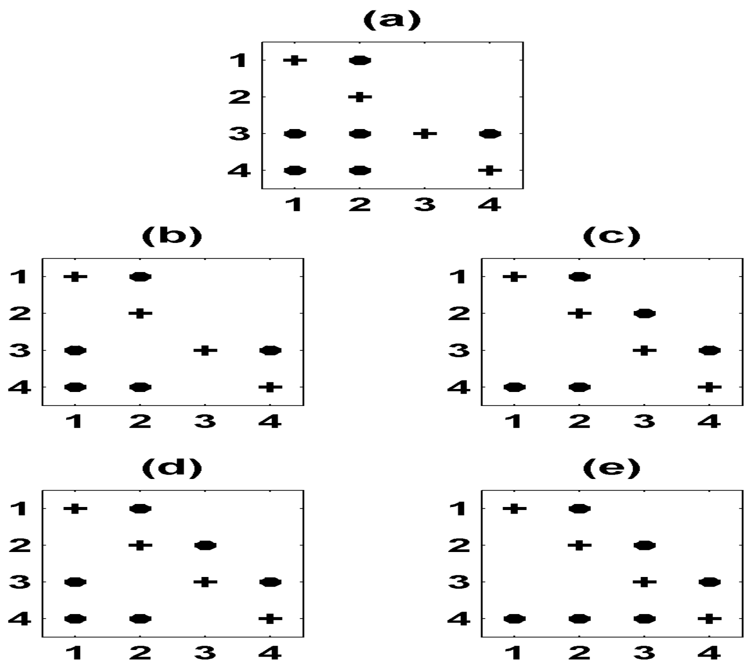

Fig. 4.10. Alternate communication topologies in the presence of communication disruption

Table 4.6
Comparison of alternate communication topologies in the presence of communication disruption

Communication Topology	SSE	Similarity Index (%)
Fig.	0.155	-
Fig	0.173	83.33
Fig.	0.169	66.66
Fig.	0.171	83.33
Fig.	0.167	66.66

4.5 Conclusions

The main bottleneck in the computational demands of the coordinated MPC algorithm is the iterative communication of information between local controllers. It is the communication overhead, that increases the overall computational demand of the C-MPC strategy. Reducing the number of communications would significantly improve the speed of convergence of the C-MPC architecture and make it quite beneficial for real world applications.The novel GA-RNGA based communication topology optimization and the implementation of the minimum information exchange based C-MPC controllers presented in this work has been shown to significantly alleviate the bottleneck in traditional coordinated control architectures. It has been shown that the demands of enabling communication between each and every local MPC can be lessened through optimizing the communication network and utilizing only those interaction models that significantly affect the overall performance of the system. This methodology is shown to significantly improve the performance of decentralized control strategies with minimal increase in computational demands (minimal communications).

The GA optimization problem is computationally intensive due to the simulation-optimization methodology followed in this work. Evaluation of each candidate in the GA optimization routine involved simulating a process over 500 time steps in order to evaluate the objective functions. The computational effort required to optimize the communication topology for the three case studies varied from 12 to 36 hours. However, as the communication structure optimization is a design problem and is performed before the implementation of the real-time C-MPC control strategy, the long computational times are permissible.

Through the analyses of multiple case studies, it is seen that the performance could usually be improved significantly (more than 50%) by selecting only a few interaction models. However, the selection of the interaction models needs to be optimized in order to ensure maximum performance enhancement with minimal increase in computational resources. Also, the communication topology optimization significantly improves the scalability of the C-MPC architecture for large-scale applications. The algorithm developed in this work has been used to prioritize the interactions and configure communication topologies of varying complexities successfully. The results of this work can be used to design control architectures for large-scale systems as well as provide alternate control architecture to existing systems in the presence of communication disruptions.

The results of this work provide the operator with an easy to understand trade-off chart depicting the achievable performance enhancement and the associated computational demands. Based on operational demands, the desired complexity in the communication topology is selected and the corresponding optimized interaction configuration is implemented. Since GA was used to solve the designed multi-objective optimization problem; a set of pareto optimal solutions was developed, providing additional flexibility to the operator. Moreover, The GA based selection algorithm, though globally optimal is computationally intensive. In this work, the utility of an *a priori* interaction quantifier namely RNGA has been shown to reduce the GA search space exponentially without compromising excessively on the controller performance.

Chapter 5

APPLICATION OF COORDINATED MODEL PREDICTIVE CONTROL FOR MULTI-RESERVOIR MANAGEMENT SYSTEMS

5.1 Introduction

Mulit-reservoir networks are large-scale systems spread across vast geographical areas and are made up of a number of smaller, heterogeneous, interacting subsystems. The presence of different multiple authorities, each one governing one or few sub-systems, can provide a strong resistance towards adopting centralized controllers, even when they can be technically adopted. Currently, decentralized control strategies are widely implemented for the optimal management of multi-reservoir networks. Despite being widely researched and utilized in the field of process and systems engineering, the coordination of multiple model predictive controllers has not been adopted for water resources management. The use of coordinated control schemes is limited to the management of irrigation canals (Cardona et al. (1997) and Negenborn, van Overloop & De Schutter (2009)), and there have been very few theoretical studies like Niewiadomska-Szynkiewicz et al. (1996) which considered the problem of coordinated multiple for controllers for water reservoir networks operation. With the purpose of exploring the potential of the coordinated control approach for the operation of multi-reservoir networks, numerical experiments on a two reservoir network and a larger real world case study were performed and the applicability and utility of a coordinated control algorithm for the operation of water reservoir networks is explored.

5.2 Multi-Objective Two Reservoir System

The potential of the developed coordination algorithm is evaluated on a simple water system composed of two multi-purpose reservoirs in cascade and developed from a single-reservoir system first presented in Castelletti et al. (2011). The reservoirs are assumed to be cylindrical with unit surface area. The dynamics of the storage and s_t^1 and s_t^2 $[m^3]$ in the upstream and downstream reservoir is modeled with the following mass balance equations

$$s_{t+1}^1 = s_t^1 + (a_{t+1}^1 - u_t^1).\Delta \tag{5.1}$$

$$s_{t+1}^2 = s_t^2 + (q_{t+1} - u_t^2).\Delta \tag{5.2}$$

where u_t^1 and u_t^2 $[m^3/s]$ are the release decisions (controls), both belonging to the interval $[0, 60]$ m^3/s, and Δ is the integration time-step. The inflow a_{t+1}^1 $[m^3/s]$ in the interval $[t, t+1)$ to the upstream reservoir comes from an uncontrolled catchment whose behaviour is modelled with a simplified Thomas-Fiering model (Loucks et al. (1981)), namely

$$a_{t+1}^1 = \mu^1 + \rho_{flow}.(a_t^1 - \mu^1) + \sqrt{1 - \rho_{flow}^2}.(\mu^1 C_v \delta) \tag{5.3}$$

where the parameters are the mean μ^1, coefficient of variation C_v and the correlation coefficient of the streamflow ρ_{flow} (respectively equal to 40, 0.10 and 0.40), while δ is a standard normal random number. The total inflow q_{t+1} $[m^3/s]$ in the interval $[t, t+1)$ to the downstream reservoir is given by the contribution a^2_{t+1} of an uncontrolled catchment, generated with the Thomas-Fiering model (eq. 5.3 with the mean $\mu^1 = 20$) and the release from the upstream reservoir.

The reservoirs are controlled with the purpose of satisfying two objectives each, water supply (for hydropower production upstream and irrigation downstream) and flooding along the lake shores. The step-costs associated to the upstream reservoir control are thus the deficit of hydropower production, i.e.

$$g_t^{1,u} = max(4.36 - P_t,\, 0) \tag{5.4}$$

where 4.36 kWh/day is the installed capacity and P_t is the energy production, which depends on the release u_t^1 and h_t^1on the reservoir level (given by the ratio between the storage s_t^1 and the surface S, assumed to be unity); and the squared deviation from the flooding threshold $\bar{h}^1 = 50m$, i.e.

$$g_t^{2,u} = max(h_t^1 - \bar{h}^1,\, 0)^2 \tag{5.5}$$

The step-costs associated to the downstream reservoir are the squared deficit of irrigation supply, i.e.

$$g_t^{1,d} = max(\bar{i} - u_t^2,\, 0)^2 \tag{5.6}$$

where the demand $\bar{i}$ corresponds to $60m^3/s$; and the squared deviation from the flooding threshold $\bar{h}^2 = 50m$, i.e.

$$g_t^{2,d} = max(h_t^2 - \bar{h}^2,\, 0)^2 \tag{5.7}$$

where h_t^2 is the reservoir level.

The rationale behind the choice of this case study is that its relative simplicity permits to calculate the optimal solution with the centralized approach thus allowing to evaluate the effectiveness of the proposed coordination algorithm in approximating the true solutions.

Consider a water system composed by M interconnected water reservoirs, fed by C uncontrolled catchments. A network of natural and artificial canals connects the reservoirs to each other and with different water users, such as irrigation districts, hydropower plants and drinking water treatment plants. The global model, obtained by aggregating the models of the different sub-systems, is a discrete-time, nonlinear, stochastic model of the following form (Castelletti et al. (2008)):

$$\mathbf{x_{t+1}} = f_t(\mathbf{x_t}, \mathbf{u_t}, \varepsilon_{t+1}) \tag{5.8}$$

where $\mathbf{x_t} \in \mathbb{R}^{n_x}$, $\mathbf{u_t} \in \mathbb{R}^{n_u}$ and $\varepsilon_{t+1} \in \mathbb{R}^{n_\varepsilon}$ are the state, control and disturbance vectors. The state $\mathbf{x_t}$ is composed of the state variables (the storages) of the M reservoirs and the state variables of the C catchments; the control $\mathbf{u_t}$ is composed of the M release decisions (controls) from the M reservoirs; the disturbance ε_{t+1} is composed of the C random disturbances of the uncontrolled catchments models.

If a real-time centralized control strategy is adopted, the global model is employed to design a unique controller that satisfies all the control objectives associated to the M reservoirs. This means that at each time-step t, a forecast of the inflow realization from the uncontrolled catchments is provided over the finite horizon $[t, t+h]$, and the corresponding sequence of optimal decisions $\mathbf{u_t}, ., ., ., ., \mathbf{u_{t+h}}$ for the whole water system is provided by solving an open-loop optimization problem. The control algorithms for the state-space formulation was modified as given below Centralized Formulation:

$$\begin{aligned}
&J = \min_{u_t, \ldots, u_{t+h-1}} [\sum_{\tau=t}^{t+h-1} g_\tau(\mathbf{x}_\tau,\, \mathbf{u}_\tau,\, \varepsilon_{\tau+1}) + \bar{g}_{t+h}(\mathbf{x_{t+h}})] subject\ to \\
&x_{\tau+1} = f_\tau(\mathbf{x}_\tau,\ \mathbf{u}_\tau,\ \varepsilon_{\tau+1}) \\
&0 \leq \mathbf{u}_\tau \leq \mathbf{u^{max}} \\
&\mathbf{x_t}\ given
\end{aligned} \tag{5.9}$$

for each τ in the time horizon $[t, t+h]$; where $g_\tau(.)$ is a normalized step-cost function accounting for the costs associated to the state transitions, $\bar{g}_{t+h}(.)$ is a penalty function related to the final state $\mathbf{x_{t+h}}$, and $\mathbf{u^{max}}$ the maximum feasible values for the control variables. Since the problem accounts for all the control objectives, the step-cost $g_\tau(.)$ is defined by determining a convex combination of all the normalized step-costs in the water system (weighting method), i.e.

$$g_\tau(.) = \sum_{i=1}^{M*n} w^i g_\tau^i(.)\,,\ with\ \sum_{i=1}^{M*n} w^i = 1 \tag{5.10}$$

where M is the number of reservoirs in the water system, and n the number (assumed to be equal) of objectives for each reservoir. When this control strategy cannot be adopted, the control problem is often defined with a decentralized strategy, which aims at defining for each single reservoir in the water system a specific real-time control problem with the purpose of satisfying only the n control objectives. For the j^{th} reservoir this problem takes the following form:

Decentralized Formulation:

$$\begin{aligned}
&J^j = \min_{u_t^j,\ldots,u_{t+h-1}^j} [\sum_{\tau=t}^{t+h-1} g_\tau^j(x_\tau^j,\, u_\tau^j,\, \varepsilon_{\tau+1}^j) + \bar{g}_{t+h}^j(x_{t+h}^j)]\\
&subject\ to\\
&x_{\tau+1}^j = f_\tau(x_\tau^j,\ u_\tau^j,\ \varepsilon_{\tau+1}^j)\\
&0 \le u_\tau^j \le u^{max,\,j}\\
&x_t^j\ given
\end{aligned} \tag{5.11}$$

where the penalty $\bar{g}_{t+h}^j$ accounts only for the final state x_{t+h}^j and the normalized step-cost g_τ^j is now given by the convex combination of the n step-costs of the j^{th} reservoir, i.e.

$$g_\tau^j(.) = \sum_{i=1}^{M*n} w^i g_\tau^{j,\,i}(.)\,,\ with\ \sum_{i=1}^{M*n} w^i = 1 \tag{5.12}$$

The resolution of this problem is significantly smaller than the centralized problem, but is likely to lead to sub-optimal solutions, when considering the performance of the overall system. To maintain the existing decentralized structure but at the same time drive the controller performance towards a global optimum, a coordination strategy can be adopted. The coordination algorithm works towards combining the advantaged of both the centralized and decentralized control strategies while at the same time addressing their drawbacks. A decentralized control structure is maintained, but the performance is driven towards the centralized control scheme by a coordinator which enables communication and cooperation between the individual local controllers. Communication is accounted for by modifying the state transition equations to include the states and controls of all the M reservoirs in the water system, while cooperation is guaranteed by the objective function, which is modified as a convex sum of the objective functions of the individual decentralized controllers (Anand et al. (2011)). For the j^{th} reservoir the coordination problem takes the following form

Coordinated Formulation:

$$
\begin{aligned}
& J^j = \min_{u_t^j, \ldots, u_{t+h-1}^j} \sum_{j=1}^{M} \lambda_j [\sum_{\tau=t}^{t+h-1} g_\tau^j(x_\tau^j,\ u_\tau^j,\ \varepsilon_{\tau+1}^j) + \bar{g}_{t+h}^j(x_{t+h}^j)] \\
& \textit{subject to} \\
& x_{\tau+1} = f_\tau(\mathrm{x}_\tau,\ \mathrm{u}_\tau,\ \varepsilon_{\tau+1}^j) \\
& 0 \leq u_\tau^j \leq u^{max,\, j} \\
& x_t \textit{ given} \\
& \textit{where,} \\
& \sum_{j=1}^{M} \lambda^j = 1, \ \ \textit{with } \lambda^j > 0
\end{aligned}
\tag{5.13}
$$

With these modifications, each controller now solves an optimization problem with the same objective function. Though the optimization problem is the same, the resulting sequence of optimal decisions $u_t^j,\ \ldots,\ u_{t+h-1}^j$ from each controller is sub-optimal, because each controller employs a different state transition equation. To make the different controllers converge to a globally optimal solution $\mathbf{u_t},\ \ldots,\ \mathbf{u_{t+h-1}}$, the coordinator employs a direct substitution algorithm iteratively and coordinates the local controllers to convergence or a predefined maximum number of iterations.

Real-time control in the form of MPC is implemented on the two reservoirs test case to evaluate the performance of the coordination algorithm vs. the centralized and decentralized strategy. To this purpose, a Monte Carlo simulation analysis is adopted, with 100 different combinations of initial storage conditions and inflow realizations (over an horizon of 100 days) from the two uncontrolled catchments.

The value of the objective function is computed as the average (normalized) value of the step-costs on the simulation horizon, with the same weight adopted for all the control objectives: with the centralized strategy the i-th weight w^i is thus equal to 0.25, while with the decentralized and coordinated strategy a weight equal to 0.50 is adopted for the control objectives in the upstream and downstream reservoir.

5.2.1 Comparison of performance with perfect and non-perfect inflow forecast

In the first numerical experiment, the controllers are tested with a three steps ahead perfect forecast (i.e. the inflow predictions employed by the controllers are assumed to be without errors on the prediction horizon). As shown in the upper panel of Fig. 5.1, the decentralized MPC performance is suboptimal as compared to the centralized strategy, while the coordination algorithm is able to improve the performance of the controllers, driving it closer to the global optimum. The performance of the coordinated control algorithm improves with an increase in the number of iterations and in the case study presented, the maximum number of iterations was limited to 50. This was seen to significantly improve the decentralized controller performance, resulting in a performance very close to that of a centralized controller with an acceptable increase in computational cost. A non-perfect forecast of the inflow realizations, obtained by adding to these a randomly-generated noise (Sivapragasam et al. (2007)), is further employed to assess the robustness of the control algorithms. The performance, though degraded from the previous experiments, are seen to follow the same trends, with coordinated MPC improving the existing decentralized controller performance (upper panel in Fig. 5.1).

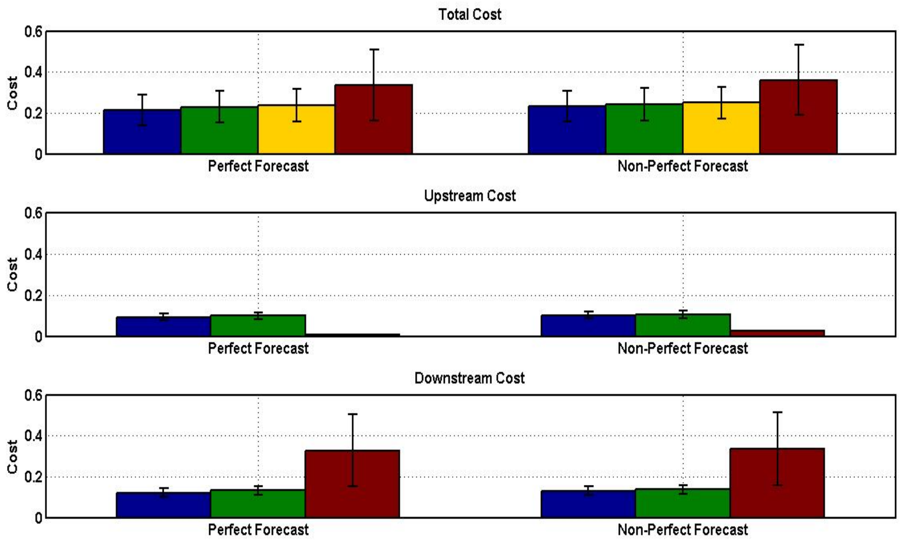

Fig. 5.1. Performance comparison (mean and variance) of total, upstream and downstream costs (upper, middle and lower panel) of centralized (blue), coordinated-50 iterations (green), coordinated-5 iterations (yellow) and decentralized (red) MPC (with perfect and non-perfect inflow forecast).

5.2.2 Comparison of costs at individual reservoirs

Fig. 5.1 (middle and lower panels) shows the total costs at the upstream and downstream reservoirs obtained with the different control strategies (perfect and non-perfect forecast). It can be noticed that the centralized control strategy provides a worse performance than the decentralized controller in the upstream reservoir. This is because the centralized controller optimizes the total cost of both the reservoirs in the system, with the risk of not guaranteeing the best performance in each sub-system, while the decentralized strategy seeks only the local optimum.

The decentralized controller ignores the effect of the upstream reservoir on the downstream reservoir and by optimizing the upstream performance locally; a high cost is incurred at the downstream reservoir. The centralized controller exploits the resources not employed by the upstream controller, improving the overall performance at the cost of the upstream reservoir. On the other hand the decentralized controller ignores the effect of the upstream reservoir on the downstream reservoir and by optimizing the upstream performance locally, a high cost is consequentially incurred at the downstream reservoir.

In this context, the coordinated control algorithm is able to significantly improve the controller performance in the upstream reservoir by explicitly accounting for the linking variables between the two reservoirs. Fig. 5.1 (middle and lower panels) also shows that the downstream reservoir contributes more to the overall costs, and the coordinated control strategy is able to improve the overall controller performances by compromising between the upstream and downstream costs.

The total costs at the upstream and downstream reservoirs obtained with the different control strategies (perfect and non-perfect forecast) as well as the overall costs are tabulated in Table 5.1 and 5.2. As seen, the decentralized MPC performance is suboptimal as compared to the centralized strategy, while the coordination algorithm is able to improve the performance of the controllers, driving it closer to the global optimum. The performance of the coordinated control algorithm improves with an increase in the number of iterations and in the case study presented, the maximum number of iterations was limited to 50. This was seen to significantly improve the decentralized controller performance, resulting in a performance very close to that of a centralized controller with an acceptable increase in computational cost.

In the presence of forecast inaccuracies, the performance though degraded from the previous experiments, are seen to follow the same trends, with coordinated MPC improving the existing decentralized controller performance.

Table 5.1
Performance Indices for the two reservoir system with a perfect inflow

Control Algortithm	**Upstream Cost**	**Downstream Cost**	**Total Cost**
Centralized MPC	0.091	0.121	0.212
Coop Based MPC (5 iteration)	0.102	0.135	0.237
Coop Based MPC (50 iteration)	0.098	0.131	0.229
Decentralized MPC	0.007	0.328	0.335

Table 5.2
Performance Indices for the two reservoir system with a perfect inflow

Control Algorithm	**Upstream Cost**	**Downstream Cost**	**Total Cost**
Centralized MPC	0.102	0.130	0.232
Coop Based MPC (5 iteration)	0.108	0.141	0.249
Coop Based MPC (50 iteration)	0.105	0.136	0.241
Decentralized MPC	0.025	0.335	0.360

5.3 Alqueva Multi-Reservoir System

The Alqueva reservoir network is located in the southeast of Portugal in the Alentejo region (Fig. 5.2). The design of the Alqueva project started during the early 1950s and studies and designs have been continuously developed until the political decision for the construction of the main dam (Alqueva) began in 1997. Even after this decision, the design has suffered several modifications mainly in what concerns irrigation areas, associated water volumes and crop needs. Topography is mainly plains with sparse vegetation and the region has a Mediterranean climate. The main objectives of this water system are: (i) irrigation of about 110,000 ha, (ii) drinking water supply to 170,000 inhabitants and (iii) hydropower generation, with the main dam presenting two reversible groups of 129.6 MW. The Alqueva dam is responsible for the creation of the largest reservoir in Western Europe with a surface area of about 250 km^2 and a maximum storage capacity of 4150 hm^3. Its primary inflow is the river Guadiana that flows North-South in Portuguese territory. The Guadiana river flow has strong seasonal variations: typical wet season river flows can reach 500 m^3/s or more, whereas dry season flows usually drops to values below $20m^3/s$.

The irrigation network has three different sub-systems: the longer one (Alqueva sub-system, corresponding to about 62,000 ha of irrigation area) with its water intake in the Alqueva reservoir and the other two in the downstream reservoir. In this work, the implementation of the coordination-based real-time controller is designed for the reservoirs located upstream of the Alvito reservoir (Figure 1) in the Alqueva sub-system. It starts at the Alamos pumping station having an installed capacity of 42 m^3/s for pumping water from Alqueva reservoir to Alamos reservoir located 79.50 m higher. An 11 km long gravity canal links this reservoir to Loureiro reservoir where a diversion for two other canals is considered: the Loureiro-Monte Novo canal

(24 km length) and the Loureiro-Alvito canal (11 km length). The first one ends in a small reservoir and the water is then pumped to Monte Novo reservoir where the principal water intake for water supply is located. During its course several water intakes for irrigation are considered. The second one, partially constructed in a tunnel delivers water to the Alvito reservoir. Water at this reservoir will be used for irrigation (it will be distributed by the downstream reservoirs of the Alqueva sub-system) and water supply.

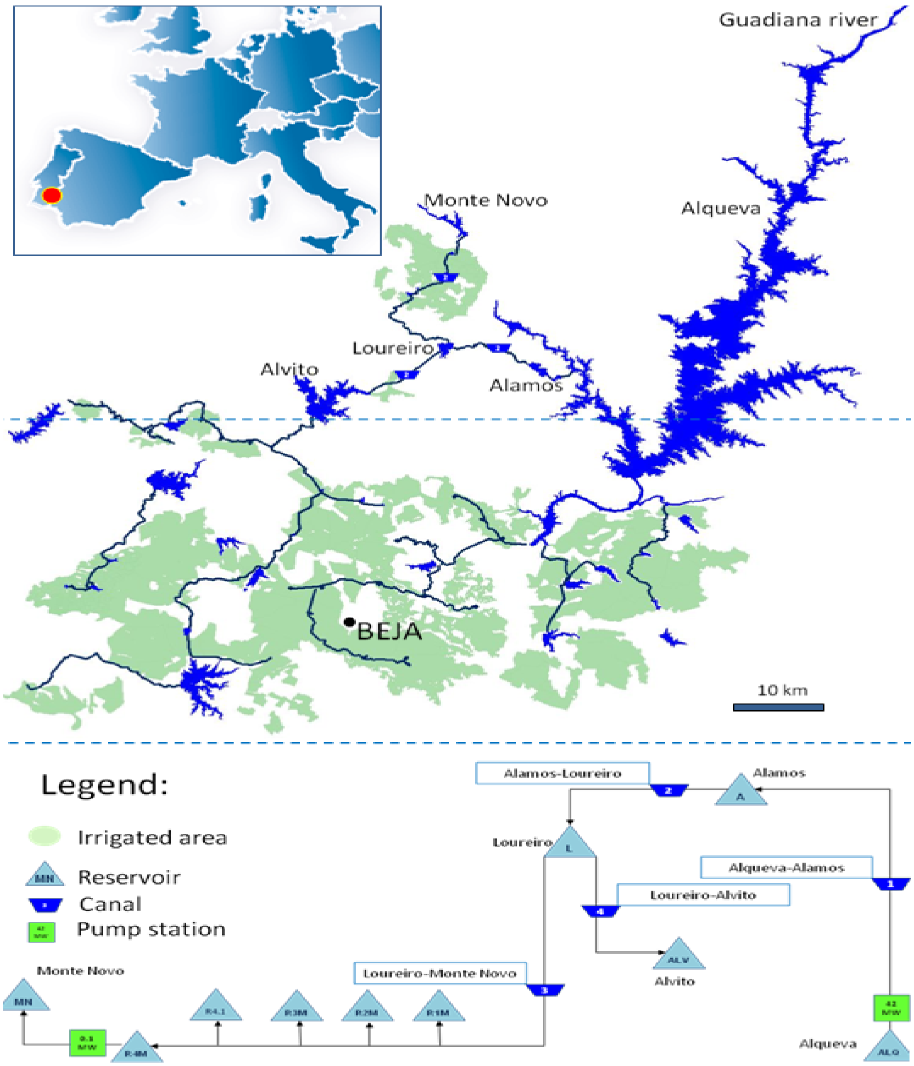

Fig. 5.2. Alqueva multi-reservoir: location and schema of the system

5.3.1 Controller Set-up

The reservoir system in the MPC is represented by a number of pool routing models with time delay operators for modeling the time lag between release from the upstream reservoir and arrival in the downstream one. The objectives on water delivery and combined energy and cost savings are translated into an objective function of the following form:

$$J = \sum_{t=1}^{M} \begin{array}{l} w^{sp}(h_t - h^{sp})^2 + w^{up}\max(h_t - h^{up}, 0)^2 + w^{down}\min(h_t - h^{down}, 0)^2 \\ +w_t^p Q_t + w^{\Delta p}(\Delta Q_t)^2 + w^{\Delta z}(\Delta dg_t)^2 \end{array} \tag{5.14}$$

where the first term penalizes deviations of the water level h from set point h^{sp}, the next two terms put an extra penalty on the level leaving an acceptable range $[h^{down}, h^{up}]$, the fourth term implements a time-depending penalty w_t^p on pumping Q_t in relation with current energy costs (gate releases are not penalized and therefore preferred), and the last two terms take care of smoothing the control trajectory by penalizing $\Delta Q_t = Q_t - Q_{t-1}$ and $\Delta dg_t = dg_t - dg_{t-1}$.

The control horizon of the MPC is 5 days with a time step of 1 hour resulting in 120 time steps. The MPC includes a total number of 4 aggregated structures, namely one pumping station and 3 outlet gate complexes, which leads to an optimization problem of 480 dimensions for the centralized control or 4 optimization problems with 120 dimensions for the coordinated control.

The MPC runs in closed loop with a detailed one-dimensional hydraulic model in SOBEK (Deltares (2010)) using a receding horizon of 6 hours. We assume forecasts of water demands in this study for focusing on the performance of the coordinated MPC approach. The only uncertainty considered is the inaccuracy of the internal model of the MPC compared to the more detailed schematization of the hydraulic model which served as a real world replacement. Hence, the controller performance in this case study is evaluated in the presence of model-plant mismatches similar to those encountered in real world applications.

SOBEK is a modeling and simulation tool used in the fields of hydrology and hydrodynamics. It is based on robust numerical methods that can be utilized for even the most complex simulations. The 1D hydraulic model is based on the equation of continuity,

$$\frac{\partial A_f}{\partial t} + \frac{\partial Q}{\partial x} = q_{lat} \tag{5.15}$$

and the conservation of momentum,

$$\frac{\partial Q}{\partial t} + \frac{\partial}{\partial x}\left(\frac{Q^2}{A_f}\right) + gA_f\frac{\partial h}{\partial x} + \frac{gQ|Q|}{C^2 R A_f} - w_f\frac{\tau_{wind}}{\rho_w} \tag{5.16}$$

where,

Q is the flow rate $[m^3/s]$

t is the time $[s]$

x is the one-dimensional coordinate $[m]$

q_{lat} is the unit side flow rate $[m^2/s]$

A_f is the wetted section area $[m^2]$

g is the acceleration due to gravity $[m/s^2]$

h is the flow depth $[m]$

C is the Chezy coefficient $[m^0.5/s]$

R is the hydraulic radius $[m]$

W_f is the surface width $[m]$

τ_{wind} is the shear stress due to wind $[N/m^2]$

ρ_w is the density of water $[kg/m^3]$

The controlled hydraulic structures are represented by a simplified structure formula with the general form (Schwanenberg & Becker (2009))

$$Q = f(h_{up}, h_{down}, dg) \tag{5.17}$$

in which dg = gate setting.

The hydraulic structures are modeled by the following formulas for a weir and an orifice with fully opened gates

$$Q = \begin{cases} \frac{2}{3}\mathrm{w_s}\sqrt{\frac{2}{3}g}(\mathrm{h_{up}}-\mathrm{z_s})^{3/2}, & \text{if } h_{up}-\mathrm{z_s}>\frac{3}{2}(\mathrm{h_{down}}-\mathrm{z_s}) \\ \mathrm{w_s}(h_{down}-z_s)\sqrt{2\mathrm{g}(\mathrm{h_{up}}-\mathrm{h_{down}})}, & \text{otherwise} \end{cases} \tag{5.18}$$

in which w_s = width of the structure, z_s = crest level. In the case of a partially or fully closed gate ($h_{up} - z_s \geq \frac{3}{2}dg$), we apply

$$Q = \begin{cases} \mathrm{w_s}\mu\, dg\sqrt{2g(h_{up} - z_s - \mu\, dg)}, & \text{if } h_{down} < \mathrm{z_s} + \mathrm{dg} \\ \mathrm{w_s}\mu\, dg\sqrt{2\mathrm{g}(\mathrm{h_{up}} - \mathrm{h_{down}})}, & \text{otherwise} \end{cases} \tag{5.19}$$

in which dg = gate setting, μ = contraction coefficient.

5.3.2 Results and Discussion

Real-time control in the form of MPC was implemented on the Alqueva reservoir system to evaluate the performance of the coordination-based algorithm against the traditional centralized strategy. When the controllers were setup in a decentralized configuration with no communication or cooperation between the controllers, the performance deteriorated significantly from that of the centralized MPC (see Table 5.3). This performance deterioration was quantified in terms of the Root Mean Square Error (RMSE), defined as the deviations of the decentralized/coordination-based control algorithms' performance (in terms of state transitions and control variables) from that of the centralized MPC. It was seen that the cooperation-based MPC algorithm was able to provide a performance similar to that of a centralized MPC strategy and by increasing the number of iterations the performance improved and asymptotically converged to the global optima (see Fig. 5.3).

In 5.3, the simulation results of the centralized MPC and 5 iterations of the coordinated MPC scheme are presented. The pump discharges at the Alamos Reservoir

Table 5.3
RMSE (with respect to the centralized MPC configuration) for the decentralized and coordination-based MPC (with different number of iterations).

Control Algorithm	**RMSE with respect to Centralized MPC**	
	Water Level	**Pump Discharge**
Decentralized MPC	0.206	2.562
Coord-MPC (1 iteration)	0.029	0.091
Coord-MPC (3 iterations)	0.023	0.068
Coord-MPC (5 iterations)	0.016	0.042

and the Loureiro Reservoir are compared across a period of 17 days. It can be observed that, the difference in schedules is not very different and the the coordinated MPC scheme is able to trace the performance of the centralized MPC (centralized MPC and coordination-based MPC trajectories overlap in most parts). By making explicit use of the linking variables between the reservoirs, the coordination-based controller is able to utilize resources ignored by the decentralized controller and approach global optimality. The dimension of the coordinated MPC is significantly smaller than that of the coordinated MPC and the communication overhead caused by the 5 iterations can be assumed to be insignificant. This shows the coordinated algorithm's applicability and effectiveness for multi-reservoir management and the results have shown that the proposed control strategy is able to provide a globally optimal solution while still retaining a decentralized structure. This would significantly reduce the computational requirements of the individual controllers and at the same time increase the reliability and robustness of the overall system.

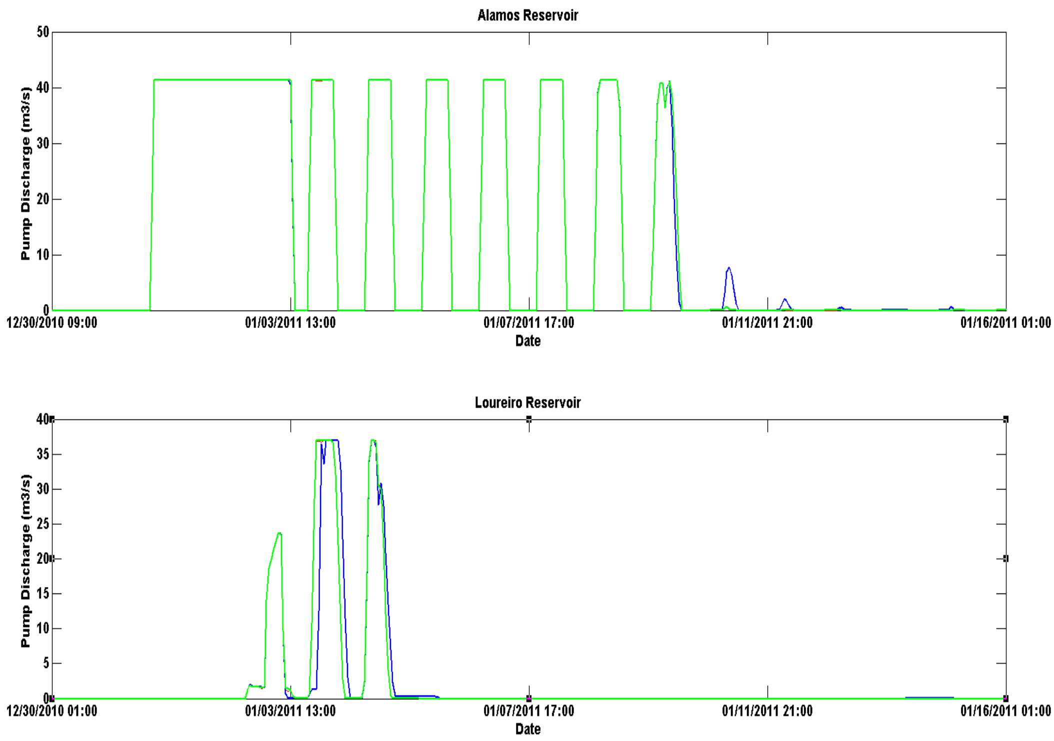

Fig. 5.3. Comparison of pump discharges of Centralized MPC (Green) and 5 Iterations of Coordinated MPC (Blue)

5.4 Conclusions

With the purpose of exploring the potential of coordination techniques for the management of large-scale water systems, we have evaluated the C-MPC algorithm on two different water management case studies. The coordination of multiple MPCs is shown to significantly improve the performance of decentralized control strategies, driving them towards the control performance of a centralized controller. The C-MPC strategy is seen to asymptotically converge to the centralized controller performance and also provide a closed-loop stable solution at each iteration. The main advantage is that it can thus be stopped at any arbitrary iteration depending on the available computational resources and desired level of performance enhancement.

In the two reservoir network, the coordinated control algorithm is able to significantly improve the controller performance in the upstream reservoir by explicitly accounting for the linking variables between the two reservoirs. It is also shown that the downstream reservoir contributes more to the overall costs, and the coordinated control strategy is able to improve the overall controller performances by compromising between the upstream and downstream costs to achieve the overall optimum.

The algorithm's applicability and effectiveness has been evaluated on a high fidelity simulator of the Alqueva reservoir system and the results have shown that the proposed control strategy is able to provide a globally optimal solution while still retaining a decentralized structure. This would significantly reduce the computational requirements of the individual controllers and at the same time increase the reliability and robustness of the overall system. Also, the inherent model-plant mismatch in the high fidelity simulator exemplifies the applicability of the C-MPC for real world systems.

While minimum information exchange is very relevant for large-scale multi-reservoir applications, the applications studied in this chapter have been explicitly used for highlighting the benefits of implementing a C-MPC control architecture. Moreover, the potential benefits of utilizing C-MPC for multi-reservoir management systems are quite evident. In the high fidelity simulator of Alqueva reservoir system, computational efforts required for coordinating the four individual controllers are practically viable. However, for larger networks, minimizing the information exchange could provide additional benefits that go beyond reducing the computational burden. The network of reservoirs are spread across cities and even countries in some cases. In these situations, the presence of different regulation authorities, each one governing one or few reservoirs, can provide a strong resistance towards adopting a centralized policy or sharing information between reservoirs. In such cases, the minimum information exchange can be used to come up with innovative solutions that exclude certain sensitive communication links and can also be used for trade-off analyses by policy makers.

Chapter 6

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH WORK

6.1 Conclusions

The focus of this research was to develop a novel coordinated model predictive control strategy that can be implemented in real-time for the control of large-scale systems. In order to achieve this, we began with a critical analysis of the existing state-of-the-art techniques in coordinated model predictive control. A comprehensive review and evaluation of the existing techniques helped identify opportunities for improvement and provided a basis for developing a new strategy.

In this research, we selected two MPC coordination strategies derived from two different schools of thought. The cooperation based coordination is based on utilizing the interaction models to enhance the performance of the decentralized control strategy. The price driven coordination strategy is based on separating the centralized control problem into a number of independent sub problems. In Chapter 3, we formulated the above mentioned coordination schemes and evaluated their performance under various scenarios.

Coordinating multiple model predictive controllers has been shown to significantly improve the performance of decentralized control strategies, driving them towards the control performance of the centralized controller. Communication of information between controllers was seen to be insufficient to guarantee closed loop stability and even in the case studies where it yielded a closed loop stable response; its performance was significantly poorer as compared to the other coordination strategies. To overcome this drawback, objective functions of the local controllers had to be modified to enable the subsystems to cooperate towards a pareto optimal solution. The price driven coordination was also seen to effectively coordinate the local controllers.

Cooperation based coordination is the only strategy that asymptotically converges to the centralized controller performance. Also, since at every iteration a closed loop stable and feasible solution is produced, it has the added advantage that it can be stopped at any arbitrary iteration depending on the available computational resources and desired level of performance enhancement. On the other hand, it was also observed that price driven coordination was able to produce the same level of performance as the cooperation based controller at a lower computational effort. While studying the robustness of the coordination algorithms, price driven coordination was found to be a more robust control strategy as it deviated less from its base performance in the presence of model-plant mismatches. In the presence of large mismatches where the cooperation based coordination failed, the price driven coordination was still able to provide a feasible and stable solution.

The system dynamics and level of interaction was also found to have a significant effect on the performance of the coordination algorithms. For systems with non-minimum phase system behavior, only the cooperation based coordination strategy was found to be closed loop stable. This necessitates a good understanding of the system dynamics before choosing an appropriate coordination algorithm, especially for systems with multivariable process zeros. This will help control practitioners to select the best coordination algorithm based on *a priori* knowledge of the system behavior and the extent of parametric uncertainties. The validity of all the empirical results described have been evaluated on both single-input single-output (SISO) and multiple-input multiple-output (MIMO) systems and it was shown that coordinated controllers were able to handle both systems efficiently. While both coordination algorithms had their advantages and drawbacks, in this work, the cooperation based coordination selected and utilized. The main advantages of utilizing the cooperation based coordination strategy was the guaranteed stability and feasibility. Also, the iterative procedure utilized in the cooperation based coordination could be terminated at any iteration and still result in a solution that was closed-loop stable and feasible. Moreover, the formulation of this coordination strategy was very flexible and facilitated the implementation of minimum information exchange based communication topologies.

While coordinating multiple controllers improves the closed loop performances of decentralized controllers significantly, it comes at the cost of increased communication between the controllers and a higher computational effort. In order to tackle this drawback, a novel GA based communication topology optimization was formulated and the implementation of the minimum information exchange based C-MPC controllers demonstrated in Chapter 4. It has been shown that the demands of enabling communication between each and every local MPC can be lessened through optimizing the communication network and utilizing only those interaction models that significantly affect the overall performance of the system. This methodology was shown to significantly improve the performance and robustness of decentralized control strategies.

The multiple case studies considered in Chapter 4 showed that the performance can often be improved significantly (more than 50%) by selecting only a few interaction models and coordinating the MPC controllers with this limited information exchange. However, the selection of the interaction models needs to be optimized in order to ensure maximum performance enhancement with minimal increase in computational resources. The GA algorithm utilized in this work helps to prioritize the interactions and configure communication topologies of varying complexities to design control architectures for large-scale systems. The results of this work can be also be used to assess the effect of communication errors and disruptions.

Since GA was used to solve the designed multi-objective optimization problem; the set of pareto optimal solutions obtained, provides additional flexibility to the control engineer. In the event of communication disruptions, the control engineer has the option of selecting the next best communication architecture from the pareto optimal solution catalog that does not utilize the disrupted communication channel. In this manner even in the event of communication delays, errors or losses; the coordinated MPC scheme would be able to utilize an appropriate communication architecture to provide a closed loop stable solution.

In addition, the computationally intensive GA based algorithm is aided by the use of an *a priori* interaction measure, RNGA, to effectively reduce the search space and facilitate quick solutions of the optimization problem without compromising excessively on the overall controller performance. The RNGA helps in identifying a set of interaction models that have a significant effect on the overall performance of the system and this information is integrated into the GA search problem. The combined GA-RNGA based topology optimization of the C-MPC architectures has shown to improve the closed loop performance significantly with minimum information exchange between controllers.

The results of this work provide the control engineer with an easy to understand trade-off chart depicting the achievable performance enhancement and the associated computational demands. Based on operational demands, the desired complexity in the communication topology can be selected and the corresponding optimized interaction configuration implemented.

The applicability of the MPC coordination algorithms for real world systems is evaluated through two case studies that explore the potential of the coordination techniques for the real-time management of large-scale water systems (Chapter 5). A numerical case study involving two reservoirs was simulated under different scenarios of the inflow realizations and the results showed that the proposed control strategy can outperform existing decentralized real-time controllers. In the two reservoirs network, the coordinated control algorithm was able to significantly improve the controller performance in the upstream reservoir by explicitly accounting for the linking variables between the two reservoirs. It is also shown that when the downstream reservoir contributed more to the overall costs, the coordinated control strategy was able to improve the overall controller performances by compromising between the upstream and downstream costs to achieve the global optimality. Through the numerical simulation studies, it is also observed that the increase in computational demand required for communication and cooperation is significantly lower than a centralized control strategy, making the application of such a strategy a very attractive prospect.

In the final phase of this work, the coordinated MPC algorithm was implemented and evaluated on a model of the Alqueva reservoir system in Portugal. A detailed, high fidelity hydraulic model of the multi-reservoir system was developed in SOBEK and served as a proxy for the real world system. When the controllers were setup in a decentralized configuration with no communication or cooperation between the controllers, the performance deteriorated significantly from that of the centralized MPC. It was seen that the cooperation based MPC algorithm was able to provide a performance similar to that of a centralized MPC strategy and by increasing the number of iterations the performance improved and asymptotically converged to the global optima. It can be observed that, while there is a marked difference between the pump schedules of the centralized and decentralized control schemes, the coordination-based controller is able to provide a solution very similar to that of the centralized controller. By making explicit use of the linking variables between the reservoirs, the coordination-based controller is able to utilize resources ignored by the decentralized controller and approach global optimality. The proposed control strategy is able to provide a globally optimal solution while still retaining a decentralized structure.

6.2 Contributions of this thesis

The key contributions of this dissertation are summarized below:

- Three MPC coordination strategies derived from different schools of thought, namely the 'Communication-based Coordination', 'Cooperation-based Coordination' and the 'Price Driven Coordination' have been reformulated for systems represented by transfer functions and are presented in this work.

- The three coordination strategies were comprehensively evaluated and their benefits and drawbacks have been discussed in detail.

- The applicability of MPC coordination strategies on both SISO and MIMO systems has been demonstrated.

- The effect of model-plant mismatch on the performance of the different coordination strategies has been assessed.

- The cooperation-based coordination has been proposed as a useful algorithm to coordinate multiple model predictive controllers and the theoretical developments have been supported by simulation studies.

- The problem of alleviating the computational bottleneck caused by the C-MPC communication architecture has been addressed by developing a novel genetic algorithm based communication topology optimization that minimizes the information exchange in C-MPC controllers without significantly compromising on the overall performance.

- In order to decrease the computational load of the GA search algorithm, an *a priori* interaction quantifier was identified. RNGA was found to be an apt interaction indicator that enabled the reduction of the GA search space.

- It is also shown that the catalog of pareto optimal solutions produced by the GA-RNGA scheme can also be used to tackle communication errors and disruptions.

- The applicability of the C-MPC schemes on water management systems has been demonstrated through the implementation of the developed control architecture on a high fidelity multi-reservoir simulator.

6.3 Recommendations for Future Work

As with any research, while several questions have been posed and answered, new questions also do arise. A few possible directions for future research are highlighted below.

6.3.1 Handling Coupled Input Constraints

In the current work, the MPC coordination algorithm guarantees convergence to global optima only when the input constraints between subsystems are uncoupled. In the presence of coupled constraints, each controller provides a closed loop stable response; however the performance deteriorates and does not converge to the performance of the centralized controller. Moreover, in real world systems, the presence of severe dynamic coupling and hard bounds on the controlled variables are common. In such cases, one possible alternative would be for each controller to modify its local optimization problem and increase the decision variable set to include all coupled variables. However this will increase the dimensionality of the local optimization problems and in the case of a completely coupled system, each local MPC would need to solve the centralized MPC problem. This would increase the computational load on the local MPCs tremendously making them practically infeasible. Further research is required to assess and quantify the performance deterioration caused by coupled constraints. Also, optimization schemes that can modify the local objectives without increasing the dimensionality of the problem and yet converge to global optima need to be investigated.

6.3.2 Data-based Interaction Analysis and Adaptive Minimum Information Exchange Schemes

When the coordinated control algorithms are implemented in large-scale networked systems, the coordinator will have to process a large amount of data. Along with the tremendous computational effort required for this, the reliability of the coordinator could also be compromised. To reduce the communication load on the coordinator, a minimum information exchange based design has been developed using interaction models. In addition to the model-based interaction analysis, data-based interaction analysis which will utilize real-time process data to dynamically quantify the interaction effects and use these measures to develop a minimal information exchange based coordinated control algorithm would be valuable. The initially developed models for most systems are valid only around the modeled operating conditions and the models may become invalid because of changes such as catalyst deactivation, fouling of surfaces and product grade transitions. In this work, the effect of model-plant mismatch has been studied and it is seen that over certain mismatch thresholds, coordination is not possible. One alternative would be to develop a catalog of models for different operating conditions (based on real-time data and closed loop identification techniques) and enable the local MPCs to switch models based on the operating conditions. Another option would be develop data-based real time interaction measures which can be used to switch between and change the information exchange topology in real time to improve the performance. The efficacy of such an adaptive minimum information exchange based coordination scheme needs to be investigated in detail.

6.3.3 Coordinating Model Predictive Controllers for Multi-rate Systems

Many large scale systems comprise of multiple process occurring at different time scales. For example, in most reservoirs the water quantity dynamics is in the order of minutes while the water quality dynamics is in the order of hours or days. This makes the coordination problem even more challenging as the integration of multiple communication and optimization time scales are required if one were concerned with both water quantity and quality objectives. There has already been research on the implementation of coordination MPC schemes on multi-rate systems. Past studies evaluated the MPC operation at the slowest computational rate and also the effect of implementing the control move optimized by the fast MPC while holding the decision of the slow MPC constant. However, the effect of such schemes on the minimum information exchange based communication topology optimization needs to be investigated. There could be a significant difference in the optimized communication topology due to asynchronous feedback between controllers. While coordination may be possible, the sensitivity of the communication topology to information availability could be significant. Future work needs to be directed towards partitioning the plant optimally based on the time scales of the different processes and coordinating the different controllers that are operating at different time scales with minimum information exchange.

Appendix A
Wegstein's Method

Wegstein's method (Wegstein (1958)) is technique popularly used for accelerating the rate of convergence of iterative procedures. The major advantage of employing this algorithm is that, even in cases where the solution iteratively diverges, Wegstein's algorithm will be able to induce convergence. Also, an added advantage of this method is that it requires a single initial point and does not involve calculating derivatives.

From one-dimensional successive substitution it is know that ,by starting at an initial value x^i we get

$$x^{i+1} = f(x^i) \tag{6.1}$$

An estimate of the function $f(x)$ can be obtained by a fitting a line through $(x^i, f(x^i))$ and $(x^{i+1}, f(x^{i+1}))$ and the slope s is given by,

$$s = \frac{f(x^{i+1}) - f(x^i)}{x^{i+1} - x^i} \tag{6.2}$$

A linear interpolation of the straight line will give the value of the function at the next point (x^{i+2})

$$f(x^{i+2}) = f(x^{i+1}) + s.(x^{i+2} - x^{i+1}) \tag{6.3}$$

At convergence, $x^{i+2} = f(x^{i+2})$, i.e.

$$x^{i+2} = f(x^{i+1}) + s.(x^{i+2} - x^{i+1}) \tag{6.4}$$

Therfore,

$$x^{i+2} = f(x^{i+1})(1 - \frac{s}{s-1}) + x^{i+1}\frac{s}{s-1} \tag{6.5}$$

More generally,

$$x^{i+1} = \frac{x^{i-1}f(x^i) - x^i f(x^{i-1})}{(x^{i-1} - f(x^{i-1})) - (x^i - f(x^i))} \tag{6.6}$$

REFERENCES

Alatiqi, I. M. & Luyben, W. L. (1985), 'Alternative distillation configurations for separating ternary mixtures with small concentrations of intermediate in the feed', *Industrial & Engineering Chemistry Process Design and Development* **24**(2), 500–506.

Alatiqi, I. M. & Luyben, W. L. (1986), 'Control of a complex sidestream column/stripper distillation configuration', *Industrial & Engineering Chemistry Process Design and Development* **25**(3), 762–767.

Allgower, F. & Zheng, A., eds (2000), *Nonlinear model predictive control*, 26 edn, Birkhauser, Switzerland.

Alvarado, I., Limon, D., de la Pena, D. M. & et al. (2011), 'A comparative analysis of distributed mpc techniques applied to the hd-mpc four tank benchmark', *Journal of Process Control* **21**(5), 800–815.

Anand, A., Joshua, G., Sundaramoorthy, S. & Samavedham, L. (2011), 'Coordinating multiple model-predictive controllers for multi-reservoir management', *Proceedings of the 8th 2011 IEEE International Conference on Networking, Sensing and Control* .

Anand, A., Samavedham, L. & Sundaramoorthy, S. (2010), 'Towards coordinating local model predictive controllers for multi-reservoir management', *Proceedings of the 5th International Symposium on Design, Operation and Control of Chemical Processes* .

Anand, A., Samavedham, L. & Sundaramoorthy, S. (2012), 'Comparative performance analysis of coordinated model predictive control schemes in the presence of modelplant mismatch', *Industrial & Engineering Chemistry Research* **51**(24), 8273–8285.

Aske, E. M. B., Strand, S. & Skogestad, S. (2008), 'Coordinator mpc for maximizing plant throughput', *Computers & chemical engineering* **32**(1), 195–204.

Badwe, A., Gudi, R., Patwardhan, R., Shah, S. & Patwardhan, S. C. (2009), 'Detection of model-plant mismatch in mpc applications', *Journal of Process Control* **19**(8), 1305–1313.

Badwe, A., Patwardhan, R., Shah, S., Patwardhan, S. C. & Gudi, R. (2010), 'Quantifying the effect of model-plant mismatch on controller performance', *Journal of Process Control* **20**(4), 408–425.

Bao, J., Chan, K. H., Zhang, W. Z. & Lee, P. L. (2007), 'An experimental pairing method for multi-loop control based on passivity', *Journal of Process Control* **17**(10), 787–798.

Birk, W. & Medvedev, A. (2003), A note on gramian-based interaction measures, *in* 'Proc. of the European Control Conference'.

Bristol, E. (1966), 'On a new measure of interaction for multivariable process control', *Automatic Control, IEEE Transactions on* **11**(1), 133–134.

Brown, R., Ashley, R. & Farrelly, M. (2011), 'Political and professional agency entrapment: an agenda for urban water research', *Water Resources Management* **25**(15), 4037–4050.

Camacho, E. & Bordons, C., eds (2003), *Model predictive control*, 2 edn, Springer, London.

Camponogara, E., Jia, D., Krogh, B. & Talukdar, S. (2002), 'Distributed model predictive control', *IEEE Control Systems Magazine* **22**(1), 44–52.

Cardona, J., Gómez, M. & Rodellar, J. (1997), 'A decentralized adaptive predictive controller for irrigation canals', *Proc. RIC97, Marrakech, Morocco* pp. 215–219.

Casavola, A., Papini, M. & Franzè, G. (2006), 'Supervision of networked dynamical systems under coordination constraints', *Automatic Control, IEEE Transactions on* **51**(3), 421–437.

Castelletti, A., Pianosi, F. & Restelli, M. (2011), Multi-objective fitted q-iteration: Pareto frontier approximation in one single run, *in* 'Proceedings of the 8th 2011 IEEE International Conference on Networking, Sensing and Control', Delft, The Netherlands.

Castelletti, A., Pianosi, F. & Soncini-Sessa, R. (2008), 'Water reservoir control under economics, social and environmental constraints', *Automatica* **44**(6), 1595–1607.

Cheng, R., Forbes, J. & Yip, W. (2007), 'Price-driven coordination method for solving plant-wide mpc problems', *Journal of Process Control* **17**(5), 429–438.

Cheng, R., Forbes, J. & Yip, W. (2008), 'Dantzig-wolfe decomposition and plant-wide mpc coordination', *Computers and Chemical Engineering* **32**(7), 1507–1522.

Christofides, P. D., Scattolini, R., de la Pena, D. M. & Liu, J. (2012), 'Distributed model predictive control: a tutorial review', *Proc. Chem. Process Control* **8**, 22pp.

Cui, H. & Jacobsen, E. (2002), 'Performance limitations in decentralized control', *Journal of Process Control* **12**(4), 485–494.

De Souza, G., Odloak, D. & Zanin, A. C. (2010), 'Real time optimization (rto) with model predictive control (mpc)', *Computers & Chemical Engineering* **34**(12), 1999–2006.

Deb, K., Agrawal, S., Pratap, A. & Meyarivan, T. (2000), 'A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: Nsga-ii', *Lecture notes in computer science* **1917**, 849–858.

Deltares (2010), *Sobek*, Delft, The Netherlands.

Dunbar, W. B. (2007), 'Distributed receding horizon control of dynamically coupled nonlinear systems', *Automatic Control, IEEE Transactions on* **52**(7), 1249–1263.

Farina, M. & Scattolini, R. (2011), Distributed non-cooperative mpc with neighbor-to-neighbor communication, *in* 'Proceedings of the 18th IFAC world congress', pp. 404–409.

Fatehi, A. (2011), 'Automatic pairing of large scale mimo plants using normalised rga', *International Journal of Modelling, Identification and Control* **14**(1), 37–45.

Fucai, Q., Qi, L. & Ding, L. (2001), 'Hierarchical control for large-scale systems', *Systems Engineering and Electronics, Journal of* **12**(4), 41–45.

Grosdidier, P. & Morari, M. (1986), 'Interaction measures for systems under decentralized control', *Automatica* **22**(3), 309–319.

He, M.-J., Cai, W.-J., Ni, W. & Xie, L.-H. (2009), 'Rnga based control system configuration for multivariable processes', *Journal of Process control* **19**(6), 1036–1042.

Ho, Y.-C. (2005), 'On centralized optimal control', *Automatic Control, IEEE Transactions on* **50**(4), 537–538.

Hovd, M. & Skogestad, S. (1992), 'Simple frequency-dependent tools for control system analysis, structure selection and design', *Automatica* **28**(5), 989–996.

Imer, O. C., Yüksel, S. & Başar, T. (2006), 'Optimal control of lti systems over unreliable communication links', *Automatica* **42**(9), 1429–1439.

Jia, D. & Krogh, B. (2001), 'Distributed model predictive control', *Proceedings of the IEEE American Control Conference* .

Jiang, H., Wei, M., Xu, F. & Luo, X. (2012), A dynamic relative gain array based on model predictive control, *in* 'Intelligent Control and Automation (WCICA), 2012 10th World Congress on', pp. 3340–3344.

Johansson, K. (2000), 'The quadruple-tank process: A multivariable laboratory process with an adjustable zero', *IEEE Transactions on Control Systems Technology* **8**(3), 456–465.

Kariwala, V. (2007), 'Fundamental limitations on achievable decentralized performance', *Automatica* **43**(10), 1849–1854.

Kariwala, V., Forbes, J. F. & Meadows, E. S. (2003), 'Block relative gain: Properties and pairing rules', *Industrial & engineering chemistry research* **42**(20), 4564–4574.

Keviczky, T., Borrelli, F. & Balas, G. J. (2006), 'Decentralized receding horizon control for large scale dynamically decoupled systems', *Automatica* **42**(12), 2105–2115.

Keviczky, T., Borrelli, F., Fregene, K., Godbole, D. & Balas, G. J. (2008), 'Decentralized receding horizon control and coordination of autonomous vehicle formations', *Control Systems Technology, IEEE Transactions on* **16**(1), 19–33.

Kulhavỳ, R., Lu, J. & Samad, T. (2001), Emerging technologies for enterprise optimization in the process industries, *in* 'Chemical Process Control–VI: Sixth International Conference on Chemical Process Control', pp. 352–363.

Labadie, J. W. (2004), 'Optimal operation of multireservoir systems: State-of-the-art review', *Journal of water resources planning and management* **130**(2), 93–111.

Lasdon, L. (1968), 'Duality and decomposition in mathematical programming', *IEEE Transactions on Systems Science and Cybernetics* **4**(2), 86–100.

Law, A. M. & McComas, M. G. (2000), Simulation-based optimization, *in* 'Proceedings of the 32nd conference on Winter simulation', Society for Computer Simulation International, pp. 46–49.

Lee, T. K., Chiu, M.-S. & Arkun, Y. (1998), 'Interaction measure for the selection of partially decentralized control structures', *Industrial & engineering chemistry research* **37**(12), 4734–4739.

Li, S., Zhang, Y. & Zhu, Q. (2005), 'Nash-optimization enhanced distributed model predictive control applied to the shell benchmark problem', *Information Sciences* **170**(2), 329–349.

Liu, J., Chen, X., de la Pena, D. M. & Christofides, P. (2010), 'Sequential and iterative architectures for distributed model predictive control of nonlinear process systems', *AICHE Journal* **56**(8), 2137–2149.

Liu, J., de la Pena, D. M. & Christofides, P. (2009), 'Distributed model predictive control of nonlinear process systems', *AICHE Journal* **55**(5), 1171–1184.

Loucks, D., Stedinger, J. & Haith, D. (1981), *Water Resources Systems Planning and Analysis*, Prentice-Hall, Inc., Englewood Cliffs, NJ.

Lygeros, J. (1996), Hierarchical, hybrid control of large scale systems, PhD thesis, University of California, Berkeley.

Maciejowski, J. M. (1999), 'Predictive control with constraints'.

Maestre, J., de la Pena, D. M. & Camacho, E. F. (2009), A distributed mpc scheme with low communication requirements, *in* 'American Control Conference, 2009. ACC'09.', IEEE, pp. 2797–2802.

Maestre, J. M., de la Pena, D. M. & Camacho, E. F. (2010), 'Distributed model predictive control based on a cooperative game', *Optimal Control Applications and Methods* **32**(2), 153–176.

Marcos, N., Forbes, J. & Guay, M. (2009*a*), 'Coordination of distributed model predictive controllers for constrained dynamic processes', *Proceedings of the International Symposium on Advanced Control of Chemical Processes* .

Marcos, N., Forbes, J. & Guay, M. (2009*b*), 'Distributed linear quadratic control of large-scale processes via prediction-driven coordination', *Proceedings of the 8th World Congress of Chemical Engineering* .

Marler, R. T. & Arora, J. S. (2004), 'Survey of multi-objective optimization methods for engineering', *Structural and multidisciplinary optimization* **26**(6), 369–395.

McAvoy, T. J. (1983), 'Some results on dynamic interaction analysis of complex control systems', *Industrial & Engineering Chemistry Process Design And Development* **22**(1), 42–49.

Mesarovic, M. D. (1970), 'Multilevel systems and concepts in process control', *Proceedings of the IEEE* **58**(1), 111–125.

Mesarovic, M., Macko, D. & Takahara, Y. (1970), 'Two coordination principles and their application in large scale systems control', *Automatica* **6**(2), 261–270.

Monshizadeh-Naini, N., Fatehi, A. & Khaki-Sedigh, A. (2009), 'Input- output pairing using effective relative energy array', *Industrial & Engineering Chemistry Research* **48**(15), 7137–7144.

Morari, M. & H Lee, J. (1999), 'Model predictive control: past, present and future', *Computers & Chemical Engineering* **23**(4), 667–682.

Negenborn, R. & Maestre, J. (2014), 'Distributed model predictive control: An overview and roadmap of future research opportunities', *Control Systems, IEEE* **34**(4), 87–97.

Negenborn, R. R., De Schutter, B. & Hellendoorn, H. (2006), Multi-agent model predictive control of transportation networks, *in* 'Networking, Sensing and Control, 2006. ICNSC'06. Proceedings of the 2006 IEEE International Conference on', IEEE, pp. 296–301.

Negenborn, R. R., De Schutter, B. & Hellendoorn, J. (2008), 'Multi-agent model predictive control for transportation networks: Serial versus parallel schemes', *Engineering Applications of Artificial Intelligence* **21**(3), 353–366.

Negenborn, R. R., Promotiecommissie, S., Voorzitter, R. M., De, I. B. et al. (2007), 'Multi-agent model predictive control with applications to power networks'.

Negenborn, R. R., van Overloop, P.-J. & De Schutter, B. (2009), Coordinated distributed model predictive reach control of irrigation canals, *in* 'Proceedings of the European Control Conference', pp. 1420–1425.

Negenborn, R., van Overloop, P., Keviczky, T. & Schutter, B. D. (2009), 'Distributed model predictive control for irrigation canals', *Networks and Heterogeneous Media* **4**(2), 359–380.

Negenborn, R., van Overloop, P. & Schutter, B. D. (2010), 'Coordination of local controllers in large-scale water systems', *Proceedings of the 9th International Conference on Hydroinformatics* .

Niewiadomska-Szynkiewicz, E., Malinowski, K. & Karbowski, A. (1996), 'Predictive methods for real-time control of flood operation of a multireservoir system: Methodology and comparative study', *Water Resources Research* **32**(9), 2885–2895.

Ogunnaike, B., Lemaire, J., Morari, M. & Ray, W. (1983), 'Advanced multivariable control of a pilot-plant distillation column', *AIChE Journal* **29**(4), 632–640.

Ohshima, M., Ohno, H. & Hashimoto, I. (1995), Model predictive control: Experiences in the university-industry joint projects and statistics on mpc applications in japan, *in* 'International workshop on predictive and receding horizon control', pp. 1–16.

Pappas, G. J., Lafferriere, G. & Sastry, S. (2000), 'Hierarchically consistent control systems', *Automatic Control, IEEE Transactions on* **45**(6), 1144–1160.

Pianosi, F. & Galelli, S. (2010), Neural network and evolutionary algorithms for water resources management, *in* '9th International Conference on Hydroinformatics', Tianjin (China).

Pianosi, F. & Soncini-Sessa, R. (2009), 'Real-time management of a multi-purpose water reservoir with a heteroschedastic inflow model', *Water Resources Research* **45**(W10430), –.

Prett, D. M. & García, C. E. (1988), 'Fundamental process control'.

Qin, S. & Badgwell, T. (2003), 'A survey of industrial model predictive control technology', *Control Engineering Practice* **11**(7), 733–764.

Qin, S. J. & Badgwell, T. A. (1997), An overview of industrial model predictive control technology, *in* 'AIChE Symposium Series', Vol. 93, New York, NY: American Institute of Chemical Engineers, 1971-c2002., pp. 232–256.

Qin, S. J. & Badgwell, T. A. (2000), An overview of nonlinear model predictive control applications, *in* 'Nonlinear model predictive control', Springer, pp. 369–392.

Rangaiah, G. P. (2008), *Multi-objective optimization: techniques and applications in chemical engineering*, Vol. 1, World Scientific.

Rantzer, A. (2009), 'Dynamic dual decomposition for distributed control', *Proceedings of the American Control Conference* .

Rawlings, J. & Stewart, B. (2008), 'Coordinating optimization based controllers: New opportunities and challenges', *Journal of Process Control* **18**(9), 839–845.

Richards, A. & How, J. (2007), 'Robust distributed model predictive control', *International Journal of Control* **80**(9), 1517–1531.

Rosinova, D. & Markech, M. (2008), 'Robust control of a quadruple tank process', *ICIC Express Letters* **2**(3), 231–238.

Salgado, M. E. & Conley, A. (2004), 'Mimo interaction measure and controller structure selection', *International Journal of Control* **77**(4), 367–383.

Sandell, N., Varaiya, P., Athans, M. & Safonov, M. (1978), 'Survey of decentralized control methods for large scale systems', *Automatic Control, IEEE Transactions on* **23**(2), 108–128.

Sastry, K. (2007), 'Single and multiobjective genetic algorithm toolbox for matlab in c++', *IlliGAL Report* (2007017).

Scattolini, R. (2009), 'Architectures for distributed and hierarchical model predictive control - a review', *Journal of Process Engineering* **19**, 723–731.

Scheu, H. & Marquardt, W. (2009), Literature survey on hierarchical and distributed nonlinear mpc, including analysis and comparison, and description of the resulting methodological framework, Technical report, Hierarchical and Distributed Model Predictive Control of Large-Scale Systems.

Schuler, S., Li, P., Lam, J. & Allgöwer, F. (2011), 'Design of structured dynamic output-feedback controllers for interconnected systems', *International Journal of Control* **84**(12), 2081–2091.

Schuler, S., Muenz, U. & Allgower, F. (2010), Optimal controller structure reduction for decentralized control, *in* 'System, Structure and Control', pp. 303–308.

Schwanenberg, D. & Becker, B. (2009), 'Rtc tools'.

Schwanenberg, D., Galelli, S. & Sheret, I. (2011), Nonlinear model predictive control for heterogeneous process models in water resources, *in* '18th IFAC World Congress', Milan, Italy.

Seborg, D. E., Mellichamp, D. A., Edgar, T. F. & Doyle III, F. J. (2010), *Process dynamics and control*, John Wiley & Sons.

Seki, H., Ogawa, M., Ooyama, S., Akamatsu, K., Ohshima, M. & Yang, W. (2001), 'Industrial application of a nonlinear model predictive control to polymerization reactors', *Control Engineering Practice* **9**(8), 819–828.

Shridhar, R. & Cooper, D. (1997), 'A tuning strategy for unconstrained siso model predictive control', *Industrial and Engineering Chemistry Research* **36**(3), 729–746.

Siljak, D. & Zecevic, A. (2005), 'Control of large scale systems: beyond decentralized feedback', *Annual Reviews in Control* **29**(2), 169–179.

Sivapragasam, C., Vasudevan, G. & Vincent, P. (2007), 'Effect of inflow forecast accuracy and operating time horizon in optimizing irrigation releases', *Water resources management* **21**(6), 933–945.

Stewart, B. T., Venkat, A. N., Rawlings, J. B., Wright, S. J. & Pannocchia, G. (2010), 'Cooperative distributed model predictive control', *Systems & Control Letters* **59**(8), 460–469.

Stewart, B., Wright, S. & Rawlings, J. (2011), 'Cooperative distributed model predictive control for nonlinear systems', *Journal of Process Control* **21**(5), 698–704.

Tamaki, H., Kita, H. & Kobayashi, S. (1996), Multi-objective optimization by genetic algorithms: A review, *in* 'Evolutionary Computation, 1996., Proceedings of IEEE International Conference on', IEEE, pp. 517–522.

Tatjewski, P. (2008), 'Advanced control and on-line process optimization in multilayer structures', *Annual Reviews in Control* **32**(1), 71–85.

van de Meene, S., Brown, R. & Farrelly, M. (2011), 'Towards understanding governance for sustainable urban water management', *Global Environmental Change* **21**(3), 1117–1127.

Venkat, A. (2006), Distributed Model Predictive Control: Theory and Applications, PhD thesis, University of Wisconsin-Madison, Wisconsin, USA.

Venkat, A., Rawlings, J. & Wright, S. (2006), 'Implementable distributed model predictive control with guaranteed performance properties', *Proceedings of the IEEE American Control Conference* .

Venkat, A., Rawlings, J. & Wright, S. (2007), *Assessment and Future Directions of Nonlinear Model Predictive Control*, 1 edn, Springer, Germany, chapter Distributed model predictive control of large-scale systems.

Wegstein, J. H. (1958), 'Accelerating convergence of iterative processes', *Communications of the ACM* **1**(6), 9–13.

Xiong, Q., Cai, W.-J., He, M.-J. & He, M. (2006), 'Decentralized control system design for multivariable processes a novel method based on effective relative gain array', *Industrial & engineering chemistry research* **45**(8), 2769–2776.

Yip, W. & Marlin, T. E. (2004), 'The effect of model fidelity on real-time optimization performance', *Computers & chemical engineering* **28**(1), 267–280.

Young, R. E., Bartusiak, R. D. & Fontaine, R. W. (2002), Evolution of an industrial nonlinear model predictive controller, *in* 'AICHE SYMPOSIUM SERIES', New York; American Institute of Chemical Engineers; 1998, pp. 342–351.

Zanin, A., Tvrzska de Gouvea, M. & Odloak, D. (2002), 'Integrating real-time optimization into the model predictive controller of the fcc system', *Control Engineering Practice* **10**(8), 819–831.

Zhang, Y. & Li, S. (2007), 'Networked model predictive control based on neighbourhood optimization for serially connected large-scale processes', *Journal of process control* **17**(1), 37–50.

Zoppou, C. (2001), 'Review of urban storm water models', *Environmental Modelling & Software* **16**(3), 195–231.

Publications & Presentations

Journal articles

1. **A. Anand**, S. Sundaramoorthy, and L. Samavedham. Comparative Performance Analysis of Coordinated MPC Schemes in the Presence of Model-Plant Mismatch, Industrial and Engineering Chemistry Research, 2012, 51, 8273–8285.

2. **A. Anand**, S. Sundaramoorthy, and L. Samavedham. Coordinating Multiple Model Predictive Controllers for Multi-Reservoir Management, Journal of Hydroinformatics, 2012, 15(2), 293–305.

3. **A. Anand**, L. Samavedham, S. Galelli, S. Sundaramoorthy. Coordinating Multiple Model Predictive Controllers with Minimum Information Exchange. (AIChE Journal - Submitted)

4. P. K. Naraharisetti, I. A. Karimi, **A. Anand**, D. Y. Lee. A Linear Diversity Constraint Application to Scheduling in Microgrids, Energy, 36 (7), 2011, 4235-4243.

Peer Reviewed Conference Papers

1. **A. Anand**, G. M. Y. Joshua, L. Samavedham and S. Sundaramoorthy. Coordinating Multiple Model Predictive Controllers for Multi-Reservoir Management. Proceedings of the 8th IEEE International Conference on Networking, Sensing and Control (ICNSC 2011); April 11-13, 2011; Delft (Netherlands).

2. **A. Anand**, S. Galelli, M. Giuliani, L. Samavedham., and D. Schwanenberg. Coordinating Multiple Model Predictive Controllers for Water Reservoir Networks Operation. Proceedings of the International Congress on Modelling and Simulation MODSIM 2011, December 12-16, 2011, Perth(Australia).

3. **A. Anand**, L. Samavedham, D. Schwanenberg, S. Galelli, J.M. Vieira, J.L. Pinho. A coordination based approach for real-time management of large-scale water systems. 10th International Conference on Hydroinformatics, July1418, 2012, , Hamburg (Germany).

4. P. K. Naraharisetti, **A. Anand**, D. Y. Lee, I. A. Karimi. A mathematical method for scheduling in microgrids. Proceedings of The 5th International Symposium on Design, Operation and Control of Chemical Processes, PSE ASIA 2010, July 25-28, 2010, Singapore.

Conference – Oral Presentations

1. **A. Anand**, G. M. Y. Joshua, L. Samavedham and S. Sundaramoorthy. Coordinating Multiple Model Predictive Controllers for Multi-Reservoir Management. Proceedings of the 8th IEEE International Conference on Networking, Sensing and Control (ICNSC 2011); April 11-13, 2011; Delft (Netherlands).

2. **A. Anand**, L. Samavedham, D. Schwanenberg, S. Galelli, J.M. Vieira, J.L. Pinho. A coordination based approach for real-time management of large-scale water systems. 10th International Conference on Hydroinformatics, July1418, 2012, , Hamburg (Germany).

Conference - Poster Presentations

1. **A. Anand**, L. Samavedham and S. Sundaramoorthy. Towards Coordinating Local Model Predictive Controllers for Multi-reservoir Management. Proceeding of The 5th International Symposium on Design, Operation and Control of Chemical Processes, PSE ASIA 2010, July 25-28, 2010, Singapore.