Optimal Overload Response in Electric Power Systems applying Model Predictive Control

Master Thesis

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Preface

The presented master thesis has been realized within the scope of my final work at the Federal Institute of Technology in Zürich.
I have always been interested in electric power systems, more specifically, I was attracted by this subject because of my positive confrontation during my studies with control theory in general and because of its emerging importance related to large-scale networks.
The master thesis has been proposed by the Power Systems Laboratory in cooperation with the Laboratory for Safety Analysis of the Department of Mechanical and Process Engineering.
I would like to thank Markus Schläpfer and Michèle Arnold for all the important help offered during my stay at the laboratory. I also would like to thank the entire Laboratory for Safety Analysis, with head Prof. Wolfgang Kröger, for giving me the resources to complete my thesis. Furthermore, I would like to thank Prof. Göran Andersson of the Power Systems Laboratory for technically affirming the research. In the following report I will show my results.

October 2, 2007

Pascal Kienast
Abstract

**Keywords:** Model Predictive Control, Blackouts, Reliability Test System 96, Cascading Failures, Distributed Agents, Communicating Agents, Electric Power System Control, Load Prediction.

The liberalization of the European interconnected network as well as new upcoming trends for integration of alternative energies cause an incredible complexity to the actual generation distribution. New risks seem to affect the reliability of the electric power system. The blackouts appeared in the last years in Europe and North America are signals that indicate the presence of cascading failures which cause severe economic and social consequences. New approaches are needed to control the propagation of outages which hardly can be stopped by a human operator. This thesis analyzes the possibility of applying a control based on predictions for the system. Firstly, on a centralized level and secondly, on a decentralized level, with the help of communicating and interacting agents. The aim is to suppress failures and to minimize costs due to generation and load power redispatch.
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Overview

Model Predictive Control is a feedback control based on predictions of the system state. From the knowledge of the future state, load and generation redispatching costs can be saved for the prevention of cascading failures. Violations are eliminated before a subsequent outage occurs [8]. Firstly, Model Predictive Control is implemented centrally, i.e. all parameters are known and controlled from a central unit. Secondly, a distributed multi-agent approach is implemented, we refer to this as Distributed Model Predictive Control. Agents are responsible for a given range within which they know and control their parameters. The task assigned to each agent is to solve the global control problem with limited knowledge of the overall system and limited communication abilities. The control problems are implemented on the one area IEEE Reliability Test System 1996 [10].

To provide an overview of the thesis, a short summary of each chapter is given:

- **Chapter 1:**
  A brief introduction to the thesis is given

- **Chapter 2:**
  Basics of controlling a power plant and a general Model Predictive Control introduction is presented

- **Chapter 3:**
  The IEEE Reliability Test System 1996 is described

- **Chapter 4:**
  Model Predictive Control is centrally implemented, analyzed and simulated

- **Chapter 5:**
  The distributed Model Predictive Control approach is implemented, analyzed and simulated

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<td>$H_p$</td>
<td>Prediction Horizon</td>
</tr>
<tr>
<td>$s(k)$</td>
<td>Set-point Trajectory</td>
</tr>
<tr>
<td>$r(k)$</td>
<td>Reference Trajectory</td>
</tr>
<tr>
<td>$y(k)$</td>
<td>Current Time Output</td>
</tr>
<tr>
<td>$L(k)$</td>
<td>Discrete Load Distribution Curve</td>
</tr>
<tr>
<td>$u(k)$</td>
<td>System Input</td>
</tr>
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<td>$\hat{u}(k+i</td>
<td>k)$</td>
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<td>$\hat{L}(k)$</td>
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<tr>
<td>$P_i$</td>
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<td>$\hat{P}_{TL}$</td>
<td>Absolute Power Flow Prediction</td>
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<td>$P_{i,k}$</td>
<td>Predicted Power Flow on Branch $i$ at Time $k$</td>
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<td>Maximal Power Flow on Transmission Line $i$</td>
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<tr>
<td>$\Theta_n$</td>
<td>Voltage Angle at Busbar $n$</td>
</tr>
<tr>
<td>$C(G, L)$</td>
<td>Cost Function</td>
</tr>
<tr>
<td>$\Delta P_{G,n}$</td>
<td>Control Variable for Generator $n$</td>
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<tr>
<td>$\Delta P_{L,n}$</td>
<td>Control Variable for Load $n$</td>
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<td>$N_G$</td>
<td>Number of Generator Units</td>
</tr>
<tr>
<td>$N_L$</td>
<td>Number of Load Units</td>
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<tr>
<td>$P^\text{max}_i$</td>
<td>Maximal Admitted Flow on Transmission Line $i$</td>
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<td>Load on Load Unit $n$ at Time $k$</td>
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<td>$x_{km}$</td>
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<td>$\theta_i$</td>
<td>Voltage Angle at Bus $i$</td>
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<tr>
<td>Symbol</td>
<td>Description</td>
</tr>
<tr>
<td>--------</td>
<td>-------------------------------------------------</td>
</tr>
<tr>
<td>f</td>
<td>Strengthening Limitation Parameter</td>
</tr>
<tr>
<td>$c'$</td>
<td>Transposed Cost Array</td>
</tr>
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<td>$N_i$</td>
<td>Number of Iteration Processes</td>
</tr>
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<td>$\bar{F}$</td>
<td>Mean Value of Total System Cost</td>
</tr>
<tr>
<td>$C_{tot}$</td>
<td>Total System Cost</td>
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<tr>
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<td>Coefficient of Variation</td>
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<tr>
<td>$\Omega$</td>
<td>Set of Buses</td>
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<td>$w_i$</td>
<td>Weight Parameter</td>
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<td>Iteration Counter</td>
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<td>$\tilde{\delta}_{M,k,i}$</td>
<td>Control Array for Agent $M$ at Time $k$ on Iteration $i$</td>
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<tr>
<td>$k$</td>
<td>Efficiency Factor</td>
</tr>
<tr>
<td>$B$</td>
<td>Nodal Admittance Matrix</td>
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<tr>
<th>Acronym</th>
<th>Full Name</th>
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<td>Model Predictive Control</td>
</tr>
<tr>
<td>DMPC</td>
<td>Distributed Model Predictive Control</td>
</tr>
<tr>
<td>RTS-96</td>
<td>Reliability Test System 1996</td>
</tr>
<tr>
<td>ABM</td>
<td>Agent-Based Modeling</td>
</tr>
<tr>
<td>OPF</td>
<td>Optimal Power Flow</td>
</tr>
<tr>
<td>CBP</td>
<td>Cumulative Blackout Probability</td>
</tr>
<tr>
<td>STER</td>
<td>Short Time Emergency Ratings</td>
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Chapter 1
Introduction

This first chapter introduces the reader to the control problem related to large networks by sketching the ongoing application and the current research. In a second part, the main goals of the thesis are outlined and described.

1.1 Operating power networks

Electric power systems are planned, designed and built to supply the consumers with electric energy considering [3]:

- **Economy** - to maximize the net economic benefit of service
- **Quality** - to maximize the service quality
- **Reliability** - to minimize the risk of infrastructure damage
- **Environmental impact** - to minimize the impact on the environment

The three first points above constitute the basis of the optimization that power companies need to respect regarding their investments and daily operations: economic considerations need to be regarded when deciding issues about quality and security of supply of the system. Methods based on mathematical analysis and decision making theory have been of great matter to handle this optimization problem. As cheap and reliable access to electric energy is of great importance in nowadays modern society, it is not surprising that optimization theory is often applied in this field.

**Cascading failures** are a typical example for an electric grid disturbance that implies severe economical and social consequences violating most of the points enumerated at the beginning of this chapter. Prevention is mandatory for a reliable electric distribution and this can only be achieved by optimally controlling the network system.
1.2 Controlling Large-Scale Networked Systems

Traditionally, control of large networked systems is achieved by designing local, subsystem-based controllers that often ignore the interactions between the different subsystems. It is known that a decentralized control philosophy may result in poor systemwide control performance if the subsystems interact insufficiently [9]. A centralized approach is often more intuitive but largely viewed as impractical, inflexible and unsuitable for control of large-scale networked systems [17]. A standard decomposition technique of the centralized model is not sufficient to fulfill the requirements formulated in Sect. 1.1 so that distributed agents work iteratively and cooperatively towards the achievement of a common, systemwide control objective.

1.3 Model Predictive Control

Model Predictive Control (MPC) is widely recognized as high performance control technology. This model-based control strategy uses a prediction of the system to establish an appropriate control response. An interesting attribute of MPC is its ability to limit the model variables thanks to constraints. The effectiveness of MPC is dependent on a model of acceptable accuracy and the availability of fast computational resources [9]. MPC has been treated in various publications on the distributed side [5] and on the centralized side [18]. In [9] they even go a step further distinguishing three principal MPC frameworks: a centralized, a decentralized and a distributed. Best performances are obtained through the distributed MPC, considered as the most reliable solution. Communication is not always sufficient for a stable implementation, and as investigated in [9], iterations that diverge to infinity are observed.

In [8], distributed MPC is claimed to avoid the mitigation of cascading failures. The control strategy applied to the nonlinear model acts following the goal to shed small amounts of load and generation, the objective function is reduced to a linear formulation.

1.4 Aim of the Thesis

This thesis aims to observe and analyze the efficiency of Model Predictive Control (MPC) on electric power systems. Two principal well known approaches are adopted: the centralized and the distributed one. In order to achieve this goal, an already largely applied Agent Based Modelling approach is chosen, permitting investigation on complex higher order patterns such as cascading failures, islanding and blackouts.

A reliability test system is used as a platform to implement MPC, reliability
analysis is chosen to evaluate the efficiency of the implementation. If reliability can be increased without negatively affecting other operating objectives, the control method can be considered as a possible solution for the control approaches of today’s network system.
Chapter 2

Model Predictive Control Concept

This chapter introduces the concept of Model Predictive Control (MPC). Furthermore, the theoretical basics of controlling a power plant are reviewed helping to better understand the performance of MPC.

2.1 Control of Power Systems

Power systems are generally controlled as a hierarchical structure: Electricity Generation, Transmission, Distribution, and Consumption ( Loads) [2]. This means that the control system consists of a number of nested control loops that control different quantities in the system. Thanks to this de-coupling, it is possible to study the different control loops individually. This facilitates the task and, with appropriate simplifications, classical standard control theory methods can be used.

The overall control task in an electric power system is to maintain the balance between electric power produced by the generators and electric power consumed by the loads at all time instants. If this balance is not kept, this will lead to frequency deviations which, if too large, will have serious impacts on the system operation. A characteristic of a power system is that the load varies significantly over the day and over the year. This consumption is normally uncontrolled. The challenging task of the different control systems of the power system is to keep the power system within acceptable operating limits so that reliability is maintained and the quantity of supply, voltage and frequency is covered. In addition, the system should be operated in an economically efficient way.
2.2 Control Theory - Basics

Each decoupled control loop described in Sect. 2.1 can be analyzed by standard methods from the control theory. Consider the control system in Fig. 2.1. The block $G(s)$ represents the controlled plant and also possible controllers. From this figure, the following quantities are defined:

- $r(t) =$ Reference (set) value (input)
- $e(t) =$ Control error
- $y(t) =$ Controlled quantity (output)
- $v(t) =$ Disturbance

Normally, the controller is designed assuming that the disturbance is equal to zero, but to verify the robustness of the controller, different values of $v$ must be considered.

The main problem which is solved in control theory is to keep the controlled output quantity $y(t)$ at the desired reference value $r(t)$. This most common difficulty is called tracking problem. A system that involves only controller machines is referred to as automatic control.

![Figure 2.1: Simple control system with control signals. Out of [2]](image-url)
2.3 Model Predictive Control

2.3.1 General Description

Over the last decades, MPC, as automatic control, has become the advanced control technology of choice for controlling complex, dynamic systems, in particular in the process industry [12]. The main reasons for its success are:

- It can handle multivariable control problems
- It can account for model limitations
- It allows operation close to constraints

The importance of being able to take constraints into account arises for several reasons. Most often, to guarantee the success of predictive control, the most profitable operation is obtained when running the system at a constraint, or even at more. Often these constraints are associated with direct costs. If a product has to have a minimal quality in order to be useful, the cost can usually be minimized by making its quality just minimal.

Input constraints are commonly in the form of saturation characteristics: valves within a finite range, flow rates within maximum values. They appear also in the form of rate constraints: valves and other actuators within limited slew rates.

MPC is based on iterative, finite horizon optimization of a plant model. At time $t$, the current plant state is sampled and a cost minimizing control strategy is computed for a time horizon in the future: $[t, t + T]$. Solving the minimizing problem, trajectory predictions that start from the current state and perform in the future are calculated. Only the first step of the control strategy is implemented: then the plant state is sampled again and the calculations are repeated from the current state, yielding to a new control and new predicted path.

Although MPC with finite prediction horizon is not optimal, very good results were obtained, in practice [11].

2.3.2 Agent Architectures

The use of agents is often a solution approach for the evaluation of the MPC optimization problem. In general, agents are problem solvers that have the abilities to act, sense and communicate with each other in order to solve a given problem. Agents have an information set containing their knowledge and an action set containing their skills [15].
Two architectures may be distinguished:

- a **centralized architecture**, in which there is only one central control agent,

- a **distributed agent architecture**, in which there are numerous agents that are or are not able to communicate among each another.

Most research has focused on centralized control architecture. However, since a few years, a distributed agent architecture approach is gaining more importance in various application fields. In the following subsection, two small application examples are exposed to better clarify these two concepts.

### 2.3.3 Model Predictive Control Application:

In this subsection we consider the following MPC applications: driving a car as an example for centralized control, and a multi-vehicle formation as an example for a distributed implementation.

#### 2.3.3.1 Driving a Car

Driving a car can be taken as a simple optimization based control problem. The **centralized control problem** tries to minimize the distance from the desired path while obeying to constraints such as keeping the distance from the leading car, speed limitations and staying in lane. Once a prediction on the car trajectory is done, the horizon is dependent on how far into the future the control actions are planned.

#### 2.3.3.2 Multi-Vehicle Formation

In [6] interacting subsystems with decoupled dynamics and constraints are considered. A single cost function combines the subsystems into a unique control problem. A cooperative task, such as following a given trajectory or converging to a desired formation, is given. The control approach is MPC with finite prediction horizon. This control action is performed by solving online a finite horizon control problem. Due to the computation and communication requirements of solving the centralized problem a **distributed implementation** has been chosen in which each subsystem gets assigned its own control problem, that exchanges information only with neighboring subsystems.
Chapter 3

Test Bed Description

This chapter describes the test bed topology and layout for the implementation of MPC. Furthermore, a short description of the program used for the simulation is given.

3.1 Reliability Test System - 1996

As described in the [10], the IEEE Reliability Test System-1996 (RTS-96) was developed to satisfy the need of a standardized data base to test and compare results from different power system reliability evaluation methodologies. As such, the first version of RTS-96 was developed to be a reference system that contains the data and system parameters necessary to apply composite reliability evaluation methods. The RTS-96 has universal characteristics and is not representative for a specific or typical power system.

3.1.1 System Topology

The topology of the one area RTS-96 is shown in Fig. 3.1 on page 11. Since the demand for methodologies that can analyze a multi-area power systems has increased, the multi-area reliability test system has been developed by linking the single RTS-96 areas. Fig. 3.1) shows loads and generator units are shown as triangles respectively circles. The transmission line and buses are numbered as they are referred in [10].

3.1.2 System Layout

The one area RTS-96 presents the following characteristic values described accurately in [10]:
3.1.2. System Layout

24 busbars

34 transmission lines, 5 double lines

33 generation units

17 loads units

DC Voltage levels: 230/138 kV

Installed capacity: 3405 MW

Peak load: 2850 MW
3.2 Agent-Based Modeling Technique

As Markus Schläpfer describes in his paper [16], an Agent-Based Modeling (ABM) approach is applied on the RTS-96. Agents represent both technical (e.g. transmission lines) and non-technical components (e.g. grid operators) and interact with each other either directly (by exchanging information) or indirectly (via the physical network). An agent based model consists of dynamically interacting rule-based agents. The systems within which they interact can therefore create complexity, like being observed in real power systems.

Whereas analytic methods enable us to characterize the equilibria of a system, agent-based models allow us to explore the possibility of generating those equilibria. ABM can explain the emergence of higher order patterns - such as risk of cascading failures, islanding, failure propagation. Agent-based models also can be used to identify time instants in which interventions have extreme consequences and to distinguish different types of path dependency. ABM allows to integrate a comprehensive spectrum of different (stochastic) phenomena and to derive event chains as well as difficult predictable system behavior by just defining the behavioral rules of each agent and observing their interplay and thus the overall system performance.

The initial model of Markus Schläpfer [16] has been firstly simplified to a single area RTS-96 model, in that manner reducing the simulation time. Furthermore, all discrete outage events have been eliminated considering only the stochastic variation of the load. In the following subsection, a more detailed analysis on the single components of the system is exposed.

3.2.1 Busbars

In the model, busbar agents principally link loads and generation units on a single point. They get a definitively more decisive role considering the distributed approach (Chap. 5). Every busbar represents an agent responsible for the value of its generator and load units, trying to optimize cooperatively the overall problem.

3.2.2 Generating Units

Generating units are responsible to cover the requested global system load. The generator agents represent a generator which is connected via the busbar to the transmission grid. The injection of active power in the net is controlled by the control operator, described further on in Sect. 3.2.5, whose action is limited by a maximal and minimal generation power, characteristic for each generator type. The generating units are also labelled with an abstract variation cost parameter that describes the costs per MW change. The costs are enumerated in Tab. 3.1.
3.2.3 Transmission Lines

The values are arbitrary; I chose to facilitate generation power out of hydro plants making more cost expensive changes in nuclear or coal power plants.

<table>
<thead>
<tr>
<th>Unit Type</th>
<th>Unit Size (MW)</th>
<th>Unit Shedding Cost ((\frac{\text{\textdollar}}{	ext{MW}}))</th>
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<tbody>
<tr>
<td>Hydro</td>
<td>50</td>
<td>20</td>
</tr>
<tr>
<td>Coal / Steam</td>
<td>76, 155, 350</td>
<td>25</td>
</tr>
<tr>
<td>Oil / Steam / Nuclear</td>
<td>12, 20, 100, 197, 400</td>
<td>30</td>
</tr>
</tbody>
</table>

Table 3.1: Shedding cost of generating units.

3.2.3 Transmission Lines

The agent representing a transmission line consists of the branch and its protection device. If an overload is detected (line flow \(P_i\) is bigger than the admitted \(P_{i}^{\text{max}}\)), the protection device triggers the control operator, described in Sect. 3.2.5 and enters the detection state which is allowed for a maximum time span of 15 minutes. If the control operator successfully eliminates the overload, \(-P_i\) is smaller than 90\% of the \(P_{i}^{\text{max}}\), minimizing the possibility of a repeated outage- within the time limit, the device clears the alarm and returns to its initial state. Otherwise, the branch is disconnected by opening the circuit breakers. The branch tries to automatically reconnect itself if the phase angle difference \(\Delta \Theta_i\) is smaller than the preset value \(\Theta_{i}^{\text{max}}\), or after a disconnected time of one hour. Hidden malfunctions of protection devices, maintenance or failures are not considered.

3.2.4 Loads

Every load agent represents a load connected to the busbar and is controlled by the control operator. An overall hourly changing system load profile \(L(k)\) for the period of one year is implemented. The system load \(L(k)\) is distributed normally with a stochastic variance given to the system.

The control operator decides to shed load if no power can be delivered due to separation from the transmission network, due to generation shortages or because it is the only possible way to prevent cascading failures. As soon as generation capacity is available after dispatching the generation power or restoring the transmission system, the control operator gives the signal to reconnect the load. Moreover, once a certain load quantity has been shed, a time trigger of one hour recalls the control operator trying to reconnect the load.

Shedding load is supposed to a load invariant cost of 5000 per MW. It may occur that some loads are deemed more important to the system than others; this property
can be incorporated without difficulty giving each load a different shedding cost on
the same principle used with the generator units.

3.2.5 Control Operator
The control operator, considered as a controlling agent (machine), is responsible
for suppressing overloads, redistributing generation power and reconnecting or
shedding loads. Only one agent is instantiated from the system model. The control
operator becomes active in case a transmission line receives an overload message
from its protection device. It acts immediately trying to alleviate the overload solv-
ing and implementing the solution of an optimization problem. If no solution can be
found or the implementation is insufficient, the transmission line gets disconnected.
The control operator, as central unit controlling the electric power system, has a
strong effect on cascading failures, risk of blackouts and the general behavior of the
system. Exactly on this level a more intense effect analysis of different optimization
approaches is particularly interesting.

3.3 Direct Current Power Flow
The power flow is an essential part in the completeness of the steady-state model.
After each simulation step, a new power flow has to be calculated to guarantee
the continuity of the electric system. The power flow problem consists of a given
transmission network and can be suited for an alternate or direct current network.
Same as in the base model of Markus Schläpfer, the DC power flow approximation,
which ignores power losses and uses linearized equations to calculate only active
flows, is used. Since the DC power flow can be solved analytically, the calculations
are fast but the method gives no indication of what happens to voltage magnitudes,
or MVA flows. In [3], an outright mathematical derivation of the DC power flow
can be found where [19] gives a more transmission system orientated description.
The power flowing on each branch is then:

\[ P_i = \frac{1}{x_{nm}} \Theta_{nm} \]  

(3.1)

where \( x_{nm} \) is the series reactance of branch \( i \) connecting node \( n \) and node \( m \) and
\( \Theta_{nm} \) as phase angle difference \( \Theta_{nm} = \Theta_n - \Theta_m \). \( \Omega_m \) defines the quantity of busbars
connected to node \( m \).
The active power injection at bus \( n \) is thus given by

\[ P_n = \sum_{s \in \Omega_m} x_{nm}^{-1} \theta_{nm} = \left( \sum_{s \in \Omega_m} x_{nm}^{-1} \right) \theta_n + \left( \sum_{s \in \Omega_m} -x_{nm}^{-1} \theta_m \right) \]  

(3.2)
for $m=1,2,...,N$ where $N$ is the number of buses in the network. This can be put into matrix form as follows:

$$ P = B'\theta $$

where $P$ is the vector of the net injections $P_n$, $B'$ is the nodal admittance matrix with the following elements: $B'_{nm} = -x_{nm}^{-1}$, $B'_{nn} = \sum_{s\in\Omega} x_{nm}^{-1}$, and finally $\theta$ denotes the vector of voltage angles $\theta_n$. For efficiency reason a distributed approach was implemented in the base model of Markus Schläfper. Each node calculates the voltage angle $\theta_n$ in reference to its neighboring nodes, according to (3.2):

$$ \theta_n = \frac{P_n - \left(\sum_{s\in\Omega} -x_{nm}^{-1}\theta_m\right)}{\left(\sum_{s\in\Omega} x_{nm}^{-1}\right)} $$

the slack or reference bus has to be, for this calculation, omitted.

### 3.4 Anylogic

AnyLogic [20] is a simulation tool that supports discrete event, system dynamics and agent based modeling approaches. The modeling language Java enables to model the complexity of the agents at any level of details. The AnyLogic’s set of primitives and library objects allows to model interacting agents representing technical and non-technical components. The object-oriented model design provides the adequate means for large power systems. AnyLogic supports parameter variation studies, Monte Carlo simulation, sensitivity analysis and optimization. AnyLogic includes the Java release of OptQuest optimizer from OptTek, Inc. that was specifically designed to work with simulation models and supports optimization under uncertainty.
Chapter 4

Centralized Model Predictive Control

In this chapter the centralized implementation of Model Predictive Control is considered. Based on the theoretical model of MPC the application to the RTS-96 is explained. Furthermore, new concepts on state and trajectory prediction as well as on load forecasting are discussed.

4.1 Introducing Centralized Model Predictive Control

Similarly to Optimal Power Flow (OPF) described in [19] and implemented in the original version of Markus Schläpfer, the model is controlled by a central unit which possesses all information and can interfere on every level. We can solve the MPC for the minimum variation cost requiring in the meantime that the optimization calculation also balances the entire power flow at the same time. The objective function of the OPF is enlarged by the trajectory predictions depending on the control horizon.

A number of advantages make the use of a centralized approach attractive: firstly, the possibility to access and control directly every information of the model, secondly, a single agent has the ability to predict the future parameters of the model with smaller uncertainty. Some significant disadvantages come hand in hand with the advantages: in fact, tending to large systems the centralized model predictive control comes rapidly to its limits, the number of variables of which the agent has to find the optimal value increases quickly, the resources needed for computation and memory are high.
4.2 The Receding Horizon Idea

In the basic presentation of the receding horizon idea, I want to discuss the control of a single-input single-output (SISO) plant as it has similarly been done in the book of J.M. Maciejowski [12]. Assumed is a discrete-time setting and the current time is labelled as time step $k$. At the current time the plant output is $y(k)$, and the Fig. 4.1 shows the previous history of the output trajectory. Also shown is a set-point trajectory $s(t)$, which is the trajectory at the continuous time $t$. The reference trajectory $r(t|k)$ defines an ideal trajectory along which the system should return to the set-point trajectory, for instance after a disturbance occurred.

![Figure 4.1: The basic idea of receding horizon. Following curves are displayed: set-point trajectory $s(t)$, reference trajectory $r(t|k)$, plant output $y(t)$, plant output with MPC input $\hat{y}(t|k)$, plant output with no control input $\hat{y}_f(t|k)$. Source [12]](image)

A predictive controller has an internal model which is used to predict the behavior of the plant, starting at the current time $k$, over a future prediction horizon $H_p$. This prediction is called state prediction. It depends on the assumed trajectory prediction $\hat{u}(k+i|k)(i=0,1,...,H_p-1)$ that is to be applied over the prediction horizon $H_p$. The notation $\hat{u}$ indicates that at time $k$ we only have a prediction of what the input at time $k+i$ may be; the actual input at that time, $u(k+i)$, will probably be different from $\hat{u}(k+i|k)$. The principal idea is to select the input which promises the best predicted behavior. In the simplest case, we can choose the input
trajectory such as to bring the plant output at the end of the prediction horizon \( k+H_p \) to the required value \( r(k+H_p) \). There are several trajectory predictions \( \hat{u}(k|k), \hat{u}(k+1|k), \ldots, \hat{u}(k+H_p-1|k) \) which achieve this, and we could choose one of them, for example the one which requires the smallest input costs.

Once a future trajectory prediction has been chosen, only the first element of that trajectory is applied as input signal to the plant. That is, we set \( u(k) = \hat{u}(k|k) \), where \( u(k) \) denotes the actual signal applied. In a continuous control call system, one sampling interval later, the whole cycle of output measurement, prediction, and input trajectory determination, is repeated.

Since the prediction horizon remains of the same length as before, but slides along by one sampling interval at each step, this way of controlling a plant is often referred to as receding horizon strategy.

### 4.3 Control Call

Contrarily as described in the last section, where the automatic control is performed constantly, in the RTS-96 I had to choose a simplified control model, since a continuous control call would have been far too computationally expensive. The whole cycle of output measurement, prediction, and input trajectory determination is activated only when an overload of a line appears. In Fig. 4.2 the process is shown on an example of a transmission line \( i \), which touches at time \( k_1 \) the maximal flow limit of \( P_{i_{max}} \). To alleviate the problem, a control call is activated executing a MPC. The procedure terminates with the implementation of the trajectory prediction \( u(k_1) \). In this action, load must be shed which means multiple future calls of various MPCs to reconnect all loads. The set-point trajectory \( s(t) \) is now the aimed load curve \( L(t) \), where all loads are entirely connected. The reference trajectory \( r(t|k_1) \) is the fastest path to return to the set-point trajectory. The MPC is called continuously after a time lap of \( H_T \), finally at time \( k = k_1 + 5H_T \) all load is reconnected assuring a general system stability. The control process is terminated until, at time \( k_2 \), a new transmission line overload appears and an MPC is called again.

Generally spoken, as already mentioned in Sect. 3.2, an MPC is engaged as soon as an overload on a branch appears due to an inaccurate load and generation power dispatch or due to a transmission line outage. If load has been shed due to a control action, a new MPC starts after \( H_T \) trying to reallocate the load quantity. This controlling invoke induces on a highly loaded system a continuous adjustment of load and generation capacity and the system can be referred to as digital feedback controlled. On a system with little control operator calls, the adjustment are done sporadically, since rarely a transmission line is overloaded. On one side this helps to reduce significantly the simulation time, but on the other the control action gets discontinuous.
4.4 Problem Formulation

The optimization problem is formulated in such a way that it is based on one side on the Optimal Power Flow specified in the paper of Markus Schläpfer [16] and on the other side on the problem formulation described in [8].

Firstly, we have to bear in mind that as main global objective, the optimization problem has to resolve violations that appeared in the electric power system. Secondly, we desire to minimize the possibility of cascading failures. This problem can be formulated as a standard linear programming problem, using the steady-state power network equations that are ordinarily used in the OPF formulation. The decision space is any combination of load and generation shedding within the limits. The objective function is the social cost of all control actions denoted as \( C(G, L) \). Therefore, the global, single period \((H_p=1)\) control problem is stated formally as follows:

\[
\min_{\Delta P_{G, n}, \Delta P_{L, n}} \sum_{n \in (N_G+N_L)} C(\Delta P_{G, n}, \Delta P_{L, n})
\]  

(4.1)
The costs associated with shedding load (control variable $\Delta P_{L,n}$) are the social costs that would be incurred from the interruption of electric service. The costs associated for changing the generation power (control variable $\Delta P_{G,n}$) come from the amount that would have to be paid to an independent power producer for such an emergency control. $n$ is the unit index and ranges from 0 to the total number of generator units $N_G$ and from 0 to the total number of load units $N_L$. We will also encounter the control variables merged together as a single array of possible solutions:

$$\delta = (\Delta P_{G,n}, \Delta P_{L,n})^T$$

(4.2)

The objective function in (4.1) is subject to following constraints:

$$\sum_{n=0}^{N_G} \Delta P_{G,n} = \sum_{n=0}^{N_L} \Delta P_{L,n}$$

(4.3)

$$0 \leq P_{G,n} + \Delta P_{G,n} \leq P_{G,n}^{max}$$

(4.4)

$$-\Delta P_{L,n,shed} \leq \Delta P_{L,n} \leq -P_{L,n}$$

(4.5)

$$\left| P_i + \sum_{n=0}^{N_G} (a_{i,n} \Delta P_{G,n}) + \sum_{n=0}^{N_L} (a_{i,n} \Delta P_{L,n}) \right| \leq f \cdot P_{i,\max}$$

(4.6)

The balancing constraints (4.3) force the system to choose to shed load and generation in equal quantities. The inequality constraints in (4.4) and (4.5) define the action limits of the generator control variable and load control variables: the changes of all generator parameter have to be within the lower limit of a complete shut down and the upper limit of its maximal invariant value of $P_{G,n}^{max}$. The changes of all load parameter have to be between the previously shed load ($\Delta P_{L,n,shed}$) and the currently system defined load ($P_{L,n}$). The last constraint (4.6) guarantees that all sets of control actions $\delta$ do not violate the maximal accepted transmission line flows $P_{i,\max}$ of all lines $i$. $f$ is a percentage parameter for strengthening the limitation. Further explanations on the linear sensitivity factors $a_{i,n}$ are given in Appendix A.1. In the following chapter we will add a time component, which for the moment, can be omitted, so that all constraints need to be fulfilled only at time $k = 0$ ($\Delta P_{G,n}$ can also be written as $\Delta P_{G,n,k=0}$).

### 4.4.1 Objective Function

The linear-difference objective function in [8] is taken as base for all cost functions:

$$C(\delta_k) = \sum_{k=k_0}^{T} e^{-\rho k} c^l \delta_k$$

(4.7)
4.4.1. Objective Function

in (4.7), the time dimension has already been added through the variable $k$, this means that a trajectory prediction is expected out of the optimization problem. $c'$ is the transposed cost array defined in Sect. 3.2, the generator ($c_G$) and load shedding cost ($c_L$) array is composed into an unique array: $c' = (c_G, c_L)^T$. At last, the $e^{-\rho k}$ cost addition is an integral part of the objective function outlining the importance of choosing expensive actions later in the future; cheap actions are thus discounted and receive a higher priority. The variable $\rho$ assumes in the objective function an important role between the values of -1 and 1. To warrant an efficient retraction of the shed load while keeping low generation dispatch costs, I chose to select $\rho = 1$ for generation units dispatch and $\rho = -1$ for load units dispatch. The cost factors which results out of the different $\rho$ are shown in Fig 4.3.

![Figure 4.3: Asymmetrical cost factors with $\rho = 1$ for generation units dispatch and $\rho = -1$ for load units dispatch.](image)

The linear-difference objective function would thus assume the formal format of:

$$C(\Delta P_{G,n}, \Delta P_{L,n}) = \sum_{k=k_0}^{T} (e^{-k} c'_G \Delta P_{G,n} + e^{k} c'_L \Delta P_{L,n})$$

(4.8)

The specified implementation offers the mentioned advantages, but the fact that load shedding can happen easily is to be expected since the costs are lower for small $k$.

The linear objective function simplifies the calculation deeply. On one side, the main advantage is the application of linear programming for the minimization in the optimization procedure, which guarantees a faster result than a nonlinear function, also because all constraints need to be linear and time discrete. On the other side, linear programming leads to some disadvantage: a bigger model error is to be expected from the linearization and it is common to see that an optimal solution, if one exists, is always at the boundary of feasibility [7]. The last consideration has
to be taken into account when considering the model simulation, since its solution should be considered fairly extreme.

### 4.5 Electric Load Forecasting

Load forecasting is a central and integral process of the MPC problem. It involves the accurate prediction of the magnitudes of electric load over the different periods (usually hours) of the planning horizon. The basic quantity of interest in load forecasting is typically the hourly total system load. However, load forecasting might also be expanded to daily, weekly and monthly values of the system load, peak system load and system energy.

As described in Sect. 4.2, the input values are reinforced by state prediction. The predicted load is the starting point that yields the prediction of the geographical load distribution in the electric net, which helps to calculate the predicted generator capacity. Based on the bus net injection, a prediction for the single transmission line flows can be calculated.

#### 4.5.1 Common Load Forecasting Methods

A wide range of methodologies and models for forecasting are given in the literature. According to the survey of electric load forecasting [1], the techniques can be classified into nine categories which can be resumed as following:

- Multiple regression
- Exponential smoothing
- Iterative reweighted least-squares
- Adaptive load forecasting
- Stochastic time series
- ARMAX models based on genetic algorithms
- Fuzzy logic
- Neural networks
- Knowledge-based expert systems
4.5.2 Adapted Load Forecasting Method

The majority of the techniques described in Sect. 4.5.1 are computationally expensive. Therefore, I choose to implement an adapted load forecasting method based on the knowledge of a day load curve variation. The main point is that the new designing method would be fast and efficient. As the exponential smoothing, described in [1], is based on previous data to predict the future load, the adapted forecast acts looking at a standard model day load curve given in Fig. 4.4. We call

![Load distribution in % of the maximum load in one day. Source [10]](image)

Figure 4.4: Load distribution in % of the maximum load in one day. Source [10]

the discrete load distribution curve $L(k)$, where $k$ stands for the discrete time. At a determinate hour $k = k_0$, the prediction over $T$ prediction horizons is done, sampling the difference $\Delta_k = L(k_k) - L(k_0)$ out of the load distribution curve. Further on the difference is adopted to sum it up to the actual load, resulting in a load prediction:

$$\hat{L}(k_k) = L(k) + \Delta_k$$

(4.9)

A virtual dispatcher, that distributes homogenously the load on the available generation units, returns the distribution of the predicted load to the generators, resulting in a generator prediction matrix of the following form:

$$\hat{P}_G = \begin{pmatrix} \hat{P}_{G,0,0} & \cdots & \hat{P}_{G,0,T} \\ \vdots & \ddots & \vdots \\ \hat{P}_{G,NG,0} & \cdots & \hat{P}_{G,NG,T} \end{pmatrix}$$

(4.10)
and a load prediction matrix:

\[ \hat{P}_L = \begin{pmatrix} \hat{P}_{L,0,0} & \cdots & \hat{P}_{L,0,T} \\ \vdots & \ddots & \vdots \\ \hat{P}_{L,N_L,0} & \cdots & \hat{P}_{L,N_L,T} \end{pmatrix} \]  \hspace{1cm} (4.11)

The predictions are given for each generator unit from 0 to \(N_G\) and for each load unit from 0 to \(N_L\) for every time step \(k = 0 \ldots T\). Consequently the net bus injections for each node \(n\) (\(\Delta \hat{P}_{n,k}\)) are calculated through algebraic summation. This finally leads to the transmission lines flow prediction using the formula:

\[ \hat{P}_{s,k} = \sum_{n \in \Omega_n} a_{i,n} \Delta \hat{P}_{n,k} \]  \hspace{1cm} (4.12)

where the sensitivity factors \(a_{i,n}\) are specified in the Appendix A.1. A clearly laid out matrix can be constructed as similarly done with the load and generator predictions:

\[ \hat{P}_{TL} = \begin{pmatrix} \hat{P}_{0,0} & \cdots & \hat{P}_{0,T} \\ \vdots & \ddots & \vdots \\ \hat{P}_{N_{TL},0} & \cdots & \hat{P}_{N_{TL},T} \end{pmatrix} \]  \hspace{1cm} (4.13)

### 4.6 Problem Formulation with Prediction

Once the state predictions for the entire system are given, a new formulation of the problem can be done where the objective function stays invariant but the constraints are fortified with the calculated predictions. The main idea is still to save shedding costs following the predicted changes; for example, a predicted -10MW change in a generator could be an important information for the controller if it appears that it has to shed some generator capacity approximately in that surroundings. Shedding can be done preventing unprofitable load and generator dispatching.

The control variables in (4.2) receive a time dimension giving us a decision matrix(\(\delta_k\)). The two dimensional control plan has the mentioned form:

\[ \delta_k = (\Delta P_{G,n,k}, \Delta P_{L,n,k})^T = \begin{pmatrix} \Delta P_{G,0,0} & \cdots & \Delta P_{G,0,T} \\ \vdots & \ddots & \vdots \\ \Delta P_{G,N_G,0} & \cdots & \Delta P_{G,N_G,T} \\ \Delta P_{L,0,0} & \cdots & \Delta P_{L,0,T} \\ \vdots & \ddots & \vdots \\ \Delta P_{L,N_L,0} & \cdots & \Delta P_{L,N_L,T} \end{pmatrix} \]  \hspace{1cm} (4.14)
where $n$ is the index for generator units ($0 \ldots N_G$) and for load units ($0 \ldots N_L$). As can be noticed the control time starts at $k = 0$, with respect to the time horizon $T$, hence every MPC call has its own time dimension.

Once the control variable matrix is constructed, we can enhance the constraints given in (4.3), with the load prediction matrix $\hat{P}_L$, the generator prediction matrix $\hat{P}_G$ and the flow prediction matrix $\hat{P}_{TL}$. They newly formulated constraints for time $k$ are as following:

\begin{align}
&\sum_{n=0}^{N_G} \Delta P_{G,n,k} = \sum_{n=0}^{N_L} \Delta P_{L,n,k} \quad (4.15) \\
&0 \leq \hat{P}_{G,n,k} + \sum_{t=0}^{k} \Delta P_{G,n,t} \leq P_{\text{max}}^G \quad (4.16) \\
&-\Delta \hat{P}_{L,n,\text{shed},k} \leq \sum_{t=0}^{k} \Delta P_{L,n,t} \leq -\hat{P}_{L,n,k} \quad (4.17) \\
&\left| \hat{P}_{i,k} + \sum_{n=0}^{N_G} (a_{i,n} \Delta P_{G,n,k}) + \sum_{n=0}^{N_L} (a_{i,n} \Delta P_{L,n,k}) \right| \leq f \cdot P_{i,\text{max}} \quad (4.18)
\end{align}

All predictions variable are labelled with a hat. The equality constraint (4.15) stays the same as in the previous formulation of the problem, but the inequality constraints receive the addition of the predictions. In the inequality constraint (4.16) we guarantee that each generator, also during the prediction horizon, does not overshoot the physical limitation of maximal and minimal capacity generation. To accomplish this for time $k$, we sum the past control action ($\sum_{t=0}^{k} \Delta P_{G,n,t}$). The generator prediction $\hat{P}_{G,n,k}$ help to forecast the generator unit value. Similarly, the load control actions in the inequality constraint (4.17) must take into account the past changes ($\sum_{t=0}^{k} \Delta P_{L,n,t}$) and can be chosen within limits that are given by the predicted support of $\hat{P}_{L,n,k}$. Also, in the last inequality constraint (4.18) the flow predictions $\hat{P}_{i,k}$ are incorporated and warrant no branches violations for all discrete times $0 \ldots T$. 
4.7 Results

The Centralized MPC control is finally implemented in the RTS-96 model as it is described in the last sections. An interesting variation parameter is the time horizon. As described in [12] we would expect a more stable and more reliable system behavior by increasing the prediction horizon. I mostly refer my results to the Optimal Power Flow delineated in [16]: in fact, if the horizon is reduced to $T=1$, no predictions are made and the MPC is scaled down to an OPF with a slightly different cost function.

To evidence the MPC action on the system, two different time spans are adopted. One is concentrated on a single day, following the 24 hours system load curve in Fig. 4.4, the other is based on a longer period of time. Detailed insight analysis is done on the short time span simulation, giving the possibility to observe the control actions of MPCs under load fluctuation and particular system characteristics. However, this particular simulation method is error biased and only adequate for determinant observations, for global statement we have to simulate for a bigger time span. Indeed the long term simulations offer a different analysis of the controlled system, more large-scale happenings as propagating failures and disturbance effects can be observed.

To best reflect the results of the MPC on the RTS-96 model, I chose to loose up the maximal power flow on two branches (see Appendix B); this causes a more overload affective system that enables a repetitive call of MPCs as described in Sect. 4.3.

At this point, important information about the plots that will be shown in the further subsection, as also when it comes to the distributed approach in the next chapter are added. Some of them are based on the cost per MPC and this has to be interpreted as following: after each MPC, the load and generator shedding costs are calculated on the cost array described in Sect. 3.2, the subsequent formula defines the total shedding cost:

$$\text{Cost}(G, L) = c'_G \Delta P_{G,t=0} + c'_L \Delta P_{L,t=0}$$

(4.19)

$c'_G$ and $c'_L$ are the generator, respectively the load cost transposed cost array, $\Delta P_{G,t=0}$ and $\Delta P_{L,t=0}$ are the respective load and generation capacity to be dispatched at time $t = 0$. Once the cost have been calculated, we can calculate the distribution function for the generator or load or total shedding costs as described in Appendix A.2.

4.7.1 Simulation over One Day

At the beginning, we investigate the MPC input to the weakened RTS-96 model. The time horizon $T$ is taken as the most significant parameter. In fact, a higher prediction horizon would increase the dimension of the objective function, consider (4.7), as well as the control parameter forecast described in Sect. 4.5. A superior knowl-
edge given by a larger time horizon should optimize the control actions and reduce significantly the costs. In the first plot in Fig. 4.5 the total amount of load shed is displayed over the duration of one day for four different time horizons: $T = 1$ in blue, $T = 2$ in red, $T = 3$ in green and $T = 4$ in black. Since the control is performed on a centralized way and the predictions are exact, no outages will happen, meaning that the curve (Fig. 4.5) is exclusively given by the load shedding executed after each MPC.

Two principal observations can be made at first glance: the curves move upwards by increasing the time horizon and all curve forms look familiar to the day load curve shown in Fig. 4.4. The objective function done by a MPC with time horizon of $T = 1$ does neither present any state prediction nor trajectory prediction; this means that the optimization solution is immediately implemented, which yields to an instantaneous change in load and generator units. The bounces can be observed in Fig. 4.5, they generate undesired side actions as well as higher cost which are observed in the cumulative distribution plot in Fig. 4.6(a).

We can notice here, the clear cost optimization done by the MPC by increasing the prediction horizon $T$. Therefore, the costs are increasingly smaller due to a smoother solution of the optimization problem. However, the smoothness implies a major difficulty to settle down the curve - reconnect the load -, and higher peaks are reached. This can, for example, be noticed at 10 O’Clock. At that time all MPC curves are subject to a high load shedding in the morning hours, when it
4.7. Results

(a) MPC total cumulative probability cost. (b) MPC load cumulative probability cost.

Figure 4.6: Cumulative probability plots for MPC.

comes to reallocate the biggest number of load capacity, only the MPC with no prediction ($T = 1$) is successful. The time horizon forces a slow reallocation tending to reallocate in the future. The objective function (4.7) drives the curve to a lower level. Nevertheless, because of the possibility of computing cost expensive actions for the future, the MPC with a prediction horizon is not able to reconnect the same amount of load as the one with $T = 1$. Taking a closer look at the curves in Fig. 4.5, we can notice a slight movement to the left given by the predictive behavior of the time horizon plots for $T > 1$. In fact, the prediction aid the control parameters to fit for the most cost efficient implementation, which means an anticipate intervention. As expected, the main cause of a reduction of the total cost by augmenting the time horizon $T$ is an effect of the load cost as a consequence of the objective function described in the last sections. The cumulative load shedding cost curve is displayed in the Fig. 4.6(b). We can observe, that the curves with a prediction horizon cross at the end the curve with no prediction ($T = 1$); this is obtained by the high load and generation dispatching cost at time 8 O’Clock and 22 O’Clock.

4.7.2 Long Term Simulations

To confirm the curve tendency derived in the one day plot, long term simulations are necessary. In fact, an examination over multiple days can reduce significantly the error affliction of the curves. In all long term simulations I extended the day
load curve (Fig. 4.4) to a year load curve, as described in [10]. The simulation could now be performed for one or more years following a different day load curve every 24 hours. Generally, the load curve is fixed lower than the day load curve we considered previously, meaning that the number of MPC calls would decrease. Moreover, to better describe the general behavior during multiple days, a further plot is introduced. It is based on the cumulative probability outlined in Appendix A.2 and it is known as cumulative blackout probability (CBP) plot. This plot indicates the dimension of a blackout given in the factor load shed to demand. The simulation program has been created to log out every 5 simulation minutes, if a blackout occurs, the parameters to construct the logarithmic cumulative probability graph. The CBP is thus a filtered version of the load shedding curve in Fig. 4.5, but instead of a continuous log, only the major events are displayed and this over a discrete time grid.

![Cumulative Blackout Probability (CBP) Plot](image)

Figure 4.7: CBP for different time horizon $T$ on the weakened RTS-96 for the centralized MPC.

Since the state prediction formulated in Sect. 4.5.2 are based on a day curve load model, the calculated prediction will now be error biased, due to a different actual load curve. This effect, contrarily to the simulation over one day, causes outages and net modifications, which in the worst case may drive to cascading failure effects. Taking a closer look at the curve in Fig. 4.7, we can deduce that the statement
in the previous section were actually correct: with increasing time horizon $T$ the CBP moves higher, meaning that the probability for a certain blackout to appear is uniformly bigger. Furthermore the higher uncertainty about larger blackouts must be taken into consideration. This is due to the fact that they appear with decreasing probability. We can now conclude that with increasing time horizon $T$, the probability for a certain blackout dimension is higher. This means that the reliability decreases, because of the smoother application of MPC. However, thanks to the predictions, the dispatching costs decrease reducing significantly the operation costs.

### 4.7.3 Disturbance Effect

In addition to the long term simulation curves, we can examine a further interesting effect which is given by adding a multiplicative noise to the year load curve. This causes the ulterior difficulty to predict correctly the load. The noisy discrete load curve $\tilde{L}(k)$ is calculated as following:

$$\tilde{L}(k) = \varphi(\mu, \sigma)L(k)$$  \hspace{1cm} (4.20)

where $\varphi(\mu, \sigma)$ is the normal distribution with parameter $\mu$ and $\sigma$. In the simulation, $\mu$ and $\sigma$ were set to 1 and 0.01. Two identical simulations have been performed, one with no disturbance and a load curve of $L(k)$, the other with a normal distributed noise $\tilde{L}(k)$. The CBP results are diagrammed in Fig. 4.8; to best indicate the data density I plotted circles showing the quantity of obtained points.

As we can clearly observe the cumulative probability of a certain blackout increases uniformly with the presence of noise disturbance. The reason for that are the inexact and error based predictions formulated in Sect. 4.5.2. To suppress the prediction fault and to return to the original reliability, a better load prediction algorithm should be implemented based on one of the more computationally expensive load forecasting methods listed in subsection 4.5.1. However, this would pass beyond the scope of this thesis.
Figure 4.8: CBP for fixed time horizon $T = 2$ with noise in red and without in blue.
Chapter 5
Distributed Model Predictive Control

This chapter gives an insight into the distributed approach of Model Predictive Control outlining its communication and implementation aspects. In the first section a general introduction of the distributed MPC is done, further on the more detailed characteristics are explained and implemented in the RTS-96. At last the simulation results are shown and described.

5.1 Introducing Distributed Model Predictive Control

As already mentioned in the previous chapter, a distributed (DMPC) approach is an interesting alternative to a centralized one. Methods for solving complex problems using distributed agents are increasingly prevalent in literature, this also because of its advantages: the complex problem is split into subproblems reducing the complexity; controlling centrally a vast power network can make its system vulnerable to random failures. Last but not least a decentralized approach has the potential to solve an exception faster since each subsystem has to solve a smaller optimization problem. The distributed agent-based system is not without disadvantages. Heterogeneously distributed agents can be uncoordinated and not always observable. Furthermore, since an agent generally works with incomplete information, it makes locally correct decisions which globally may be wrong.

In [9], two different formulations for distributed MPC are specified by name: communication-based MPC and cooperation-based MPC. As described in the mentioned paper the communication-based MPC framework is prone to instability; actually, in that implementation, each subsystem’s MPC has no information about the objectives of the neighboring subsystems. In many cases, the stability cannot be
achieved and the communication-based strategy is to be considered as an unreliable strategy for systemwide control. In order to arrive at a reliable distributed MPC framework we need to ensure that the subsystems MPCs cooperate with, rather than compete against, each other for achieving system wide objectives. To guarantee convergence, it is necessary that all generated iterations are strictly systemwide feasible. In the next section, the cooperation-based MPC implementation on the RTS-96 is explained.

5.2 Agents Disposition

The basis for the cooperation-based MPC consists in the division of the global problem into several subproblems that are solved by agents. These agents are locally responsible for the generator and load units, dispatching and controlling its capacities. They are also able to reach measurements from the system through communication networks. The maximal range for agent $M$ from which information can be gathered is called control space $\Omega_M$ and it extends to every bus that can be reached by travelling over no more than $R$ branches. A high spread control space enables an agent to solve its local optimization problem with a higher grade of reliability since more local information on the development and control units are available. Each agent $M$, once its problem is solved, decides a local implementation out of the solution pool provided via communication network. Every agent sends a local solution to the neighbor lying in the solution space given by a range called communication range $R_c$.

The distribution of agents over the network can be chosen arbitrarily. I chose the most simple, but computationally most expensive solution: to place a software agent at each busbar. In the Fig. 5.1, an example for a network is shown with a random agent placement in red and its solution and control space; in this case we can extract a communication range of $R_c = 1$ and a control range of $R = 2$. Outside the defined spaces, we can notice that the agent has no interaction. Moreover external nodes are not directly measured and hence without any direct interference with the agent. This, for the agent’s unknown region is typically assumed to be connected and to be in a default state, unless it indirectly obtains other data during the cooperation process.

5.3 Problem Formulation

Similarly to the centralized implementation in Chap. 4, I start with a description of the problem giving a general idea of the process. All formulations are basically inherited from the centralized MPC, and bounded to a local subregion. The single
subproblem is therefore smaller and computationally faster to solve, but all agents are meant to find its own solutions for the overall problem. The linear-difference objective function in (4.1) receives a further parameter $M$, which stands for the agent responsible to that control space $\Omega_M$:

$$\min_{\delta_M} C(\delta_M)$$

the array $\delta_M$ is the control plan for agent $M$. For the sake of completeness, we now directly add the time component, this results in the following expression:

$$\min_{\delta_{M,k}} \sum_{k=0}^{T} C(\delta_{M,k})$$

Out of this expression, we expect a two dimensional control matrix which defines the trajectory prediction of the subproblem for discrete time $k = 0 \ldots T$, analog as the two dimensional control plan of (4.2),

Finally, we define the cost function and the constraints related to the objective function. We directly apply the linear-difference objective function taken from the
centralized approach to the symmetric cost parameter \( \rho \) as defined in (4.7) and restructure it for a local subproblem:

\[
\min_{\delta_{M,k}} \sum_{k=0}^{T} e^{-\rho k} c'_{M} \delta_{M,k} \quad (5.3)
\]

\( c'_{M} \) is here the transposed cost array for the local control plan \( \delta_{M,k} \). For each discrete time moment \( k = 0 \ldots T \) the optimization problem (5.3) is subject to the following, locally modelled, constraints:

\[
\sum_{n \in \Omega_M} \delta_{M,k} = 0 \quad (5.4)
\]

\[
0 \leq \hat{P}_{G,n \in \Omega_M,k} + \sum_{t=0}^{k} \Delta P_{G,n \in \Omega_M,t} \leq P_{G,n \in \Omega_M}^{\text{max}} \quad (5.5)
\]

\[
-\Delta \hat{P}_{L,n \in \Omega_M,\text{shed},k} \leq \sum_{t=0}^{k} \Delta P_{L,n \in \Omega_M,t} \leq -\hat{P}_{L,n \in \Omega_M,k} \quad (5.6)
\]

\[
\left| \hat{P}_{\text{net} \Omega_M,k} + \sum_{n \in \Omega_M} (a_{i,n} \Delta P_{G,n,k}) + \sum_{n \in \Omega_M} (a_{i,n} \Delta P_{L,n,k}) \right| \leq f \cdot P_{i}^{\text{max}} \quad (5.7)
\]

The first equality constraint (5.4) forces, same as in the constraint definition (4.3), to shed load and generation capacity in equal quantities. The second (5.5) and the third (5.6) constraint define the shedding boundaries taking into account the past control actions and receiving support from the predicted values (load unit \( n \) shedding prediction: \( \hat{P}_{L,n \in \Omega_M,k} \) and generator unit \( n \) shedding prediction \( \hat{P}_{G,n \in \Omega_M,k} \)) again signed with a hat. Finally, the constraint (5.7) is responsible for the fact that all the sets of generator redispatch and load shedding \( (\delta_{M,k}) \) do not overload the branches. The last constraint is bounded on a given set of transmission lines, so that not all branches are taken into consideration, but only those connected to net \( \Omega_M \) of agent \( M \). On the one side, the mentioned choice acts against achieving a global goal, but on the other side makes the system more realistic. In fact, it is absolutely possible that not all information about the transmission lines spread on the net are available for all agents.

### 5.4 Algorithm

A distributed control process is composed by various MPC calls. In my model a major agent called **MPC supervisor** is responsible for each control action performed by the single agents. The algorithm is optimally designed in the used program as a state chart. The supervisor is stated as a control unit for all single agents which
perform on each bus; in Fig. 5.2 a diagram explains the process for a MPC call. A detailed description of the algorithm is specified further on.

The algorithm can be described in words as following:

1. Once an overload appears, the MPC supervisor is activated and prepares for starting the agents.

2. In the preparation state, the general prediction matrices $\hat{P}$ (Sect. 4.5.2) and the sensitivity factors $a_{i,n}$ (Appendix A.1) are calculated.

3. Then the first agent is started, which calculates his control space on its own and collects all generator and load units variables within the range of $R$. It calculates an optimization solution based on the problem formulation in Sect. 5.3 and communicates this solution to its neighbors within a range of $R_c$.

4. The concerning agent activates its neighboring agents within a range of $R_c$ and makes an implementation choice as described in Sect. 5.5.3.

5. The MPC supervisor waits until all agents performed their iteration steps to calculate the total shedding costs: $C_{tot}$. The MPC supervisor decides if
the iteration steps should be further performed, sending to the agents the information to go on and increases the iteration counter $i$. If the conversion bound (Sect. 5.6) is reached then the process can be stopped.

5.5 Agent Cooperation

There are many ways to design cooperation into an agent network. In [13] and [14], some communication and decision-making schemes are reported. All agent cooperations are subordinate to communication rules that define the interaction among each other. Two principal implementation methods are serial and parallel. I chose a serial implementation for the preferable characteristics of the fact that this approach directly includes information from neighboring agents when it becomes available and no time gaps are present between optimization and implementation. In the next subsection I will describe the basic idea and implementation of the cascading principle, the agent activating algorithm and also the exchange of information between agents.

5.5.1 Cascading Principle

From the possibility that already available optimization solutions of single agents can be of interest to other agents that are ready to compute their optimization, a serial starting path is defined. The agents do not calculate their trajectory prediction randomly, but are conducted on the following cascading principle:

1. The MPC supervisor gives the signal to start to an agent $A$ that lies between the overloaded section and the agent which is located the most far away.
2. Once the agent $A$ solves its optimization problem and communicates the solution, it activates the agents which lie in the solution space of $A$.
3. The program chooses randomly one of the activated agents that can start and execute its optimization.
4. If there are still agents to be activated, the cascading principle continues jumping to 2, otherwise the algorithm stops.

The mentioned cascading principle offers the main advantage to supply critical agents, which are confronted with the most constrained optimization problem, with useful implementation information. Those critical agents often are located around the overloaded branch and therefore at the first point of the cascading principle the algorithm gives a start signal to an agent which is located at a certain distance, so that a solution is guaranteed. In Fig. 5.3, an example for a simple agent starting
5.5. Agent Cooperation

Figure 5.3: Agent starting cascading principle, in red the activated agents, in orange the agents which already completed their task.

cascading principle is diagrammed showing the described steps. The agent $A$ in red is activated and once it solves the optimization problem it communicates the solution to the neighboring agents in the solution space activating them (in the considered case $R_c = 1$). Once agent $A$ has completed its function, it gets orange, meaning that it computed all tasks and it is waiting for the next interaction.

5.5.2 Control Inputs Weighting

After the optimization calculation of each agent, a solution weighting is performed as described in [9]. The control variables for iteration $i$ given in $\delta_{M,k}$ for time $k = 0$ are weighted with a weight parameter $w_i$ that defines the dependency to the control variable of the last iteration $i-1$:

$$\tilde{\delta}_{M,0,i} = w_i \delta_{M,0,i} + (1 - w_i)\tilde{\delta}_{M,0,i-1}$$  \hspace{1cm} (5.8)

the weight parameter $w_i$ ranges from 0 to 1, where with a larger $w_i$ new calculated parameters are getting more important. The control array $\delta_{M,0}$ has now been upgraded with an iteration parameter $i$, defining when the array has been weighted. Simulations for optimally defining the weighting parameter $w_i$ have been performed on a base model of RTS-96. On one side, I observed quantity of convergence steps for different $w_i$, and on the other side, I analyzed the efficiency of each MPC
5.5.3 Information Exchange and Implementation

As already described, the agents present in the solution space $\Omega_M$ of agent $M$ receive the optimization solution for time $k = 0$: $\delta_{M,0}$. Of particular interest for an agent $M_m$ in the neighborhood of agent $M$ is the actual implementation that is recommended to apply, thus it contains information about the agent’s $M$ state. For example, if the mentioned agent $M$ is in a critical situation given by an overload to clear, it will redispatch as much as possible load and generation power on the bus it is concerned. But it will also ask for help to the neighboring agents such that they are able to suppress the violation. In order to reach a successful cooperation process the following implementation idea has been opted for: if there is an absolute

---

Figure 5.4: Solution weighting effects on conversion speed and DMPC efficiency; blue $w_i = 0.7$, green $w_i = 0.5$ and red $w_i = 0.3$.

---

(a) Conversion speed for different $w_i$. (b) DMPC Efficiency $k$ for different $w_i$. 

call via a percentage factor $k$ which explains the efficiency through the division between successfully solved overload problems and number of MPC calls. As it can be noticed in the bar diagram (Fig. 5.4(a)) the convergence speed in time of step quantities increases with a higher $w_i$. This means that, for one point of view, laying the importance on the newer calculated value increases the conversion speed, but, from the opposite one, a high $w_i$ implies a bigger outage risk, since the value $k$ converges to the highest value for the case $w_i = 0.7$. The simulation in Fig. 5.4(b) is performed calculating the parameter $k$ after each overload is cleared, either by a disconnection or a successful control process. The simulation has been stopped once conversion is reached. I chose for all future simulations the parameter $w_i = 0.5$ as a middle point between conversion speed and control process efficiency.
optimization solution $|\delta_{M,m,0}|$ provided by the communication network that differs more from the calculated optimization solution of the concerning agent $M$, $|\delta_{M,0}|$, implement the neighboring solution. While better implementation rules certainly exist, this rather simple cooperation algorithm achieves the proposed project goals, in fact the main thought behind it is to assure that neighbors which are unaware of a violation should implement the most cost expensive solution to be certain that the global goal is reached. Each agent may begin with severely limited information, but through the cooperation process the relevant agents obtain more detailed information about important aspects of the network.

## 5.6 Iteration Termination Condition

An iteration is completed when all agents connected to the net set $\Omega$ absolve their optimization cycle. After each iteration, new shedding costs are generated by re-dispatching load and generator units. Observing the total dispatching cost, it is possible to see that the simulation process creates a fluctuating convergence that, without guarantee, converges. As the number of iteration increases, the error bound or the confidence range decreases allowing to set a margin for terminating the iteration process.

This is based on the idea that all agents iterate and exchange information until an accord is globally found, and if we state the concordance in terms of costs, we can notice that a total cost convergence has to be observed. Effectively, if a concordance is reached every agent, from iteration process to the other, does not change its attitude and remains completely constant in the decisions made. Added up to the entire net $\Omega$ this would result in a total cost tending to a uniform constant value.

The total shedding costs are calculated adding all redispatching processes in the system:

$$C_{\text{tot}} = \sum_{m \in \Omega} c^\prime \delta_{m,0}$$

where $c^\prime \delta_{m,0}$ describes the shedding costs for bus $m$. The total costs are then the sum over all busbars connected to the net set $\Omega$.

As a convergence criterium I calculated the coefficient of variation ($\beta$) of the total cost $C_{\text{tot}}$ as described in [4]:

$$\beta = \frac{\sqrt{V(C_{\text{tot}}) / N_{i}}}{\bar{F}}$$

where $V(C_{\text{tot}})$ is the variance of the total cost between one iteration and the other, $N_{i}$ the number of iteration processes and $\bar{F}$ the mean value of total system cost.
After each iteration, a new $\beta$ is calculated. The MPC supervisor checks if $\beta$ is below the stated bound, if it is the case the iteration process is terminated, if not the iteration process proceeds.

In Fig. 5.5, the total system costs $C_{\text{tot}}$ for six characteristic example iteration processes, which start with different initial condition, are displayed after each iteration process. While processes 1, 3, 5 and 6 follow a standard iteration conversion where the error bound decreases and the convergence can be clearly stated after a defined number of iteration, the processes in curve 2 and 4 are more confused. These last cases are typical situations in which the agents can not find a concordance (case curve 2) or the system becomes instable after a certain number of steps (case curve 4) and a convergence is reached with difficulty. As I am aware of the problematic I chose 10 as the maximal number of iteration processes in the simulation, reducing the computational time and filtering any instable configurations. It is to imagine that the model implementation of an unstable situation does have impacts on the system reliability, but the fact that an unstable situation is often overcome by other MPC calls, the instability leakage may be compensated.

Figure 5.5: Example conversion of iteration processes.
5.7 Results

The DMPC is finally implemented in the RTS-96 model to analyze its behavior. Similarly as in the centralized approach, the findings are formally given as simulation results in the next subsection. On one side, we consider simulations over a single day and on the other side, we perform then over a longer term of time not necessarily defined. Furthermore, some communication results are outlined to evidence the importance of communication in the system and its effects on the test system reliability. To best compare with the centralized case, the test system (RTS-96) is also in the following simulation weakened as described in Appendix B. The description for the single plots can be extracted from Sect. 4.7 on page 26. Moreover, we also consider the cumulative blackout probability plot, already treated in the long term simulation in Sect. 4.7.2.

At this point, it has to be noted that the system enlarged by the implementation of various communicating and interacting agents becomes of a high degree of complexity, within which analytical results would be of great challenge. Furthermore, a lot of insight processes are becoming more and more difficult to observe and to display, which forces often an observation of the model as a black box. Even with those premonition, a closer look can be achieved, especially at the single day level at which interaction and communication between agents can be logged. Based on these motivations, I chose to count the number of outages within a day in the simulation, but not to disconnect the transmission lines in the grid, since this would have conducted to a modification of the network layout and, in this way, to further complexity.

5.7.1 Simulation over One Day

As we proceeded in the past chapter with the simulation of the centralized case, we begin analyzing the DMPC process control under the day curve load fluctuation (Fig. 4.4 on page 23). Also at this point the time horizon $T$ is taken as the most important variation parameter. In fact, the DMPC with no prediction, namely with time horizon $T = 1$, is not a reliable implementation. The literature has never considered it, but it is very useful for comparison with higher time horizons and with make clear how important the prediction effect in the distributed implementation is.

The load shedding over the time of one day is plotted in Fig. 5.6. If we keep in mind the same plot for the centralized implementation (Fig. 4.5) we notice how much more the DMPC varies over the time. This is due to the fact that each DMPC call is locally bounded to the initial condition, but the communication effect stirs up the entire system. The prediction effect, that can be seen if we look at the variation of the curve by increasing the time horizon $T$, can be observed also here. The larger
time horizon smooths the DMPC optimization solution reducing the total shedding cost, as it is plotted for different time horizons $T$ in Fig. 5.7(a). But it is also true that an implementation of the parameters out of the decision process does not always guarantee the successful resolution of the overload problem as stated in Tab. 5.1. In fact, the centralized approach suppresses this particularity since every implementation is subordinate to strict constraints which assure that no lines go into outage for all times $k$. However, these conditions are not valid for the distributed case, anymore. In Tab. 5.1, the DMPC calls are listed to the number of branch outages for a casual simulation procedure. Even if the results are error biased, we observe a tendency of increase in disconnections. This is, on one side, given by the parallel increase of DMPC calls for larger time horizon $T$, but, on the other side, mainly due to the implementation faults created in the communication state (Fig. 5.2). Though it is interesting to see that the biggest load shedding variation are with the time horizon $T = 1$. The higher the time horizon, the smaller the variations. In fact, this characteristic can also be observed in the total shedding

Figure 5.6: DMPC control consequences for different time horizon $T$ on the weakened RTS-96.
### 5.7. Results

<table>
<thead>
<tr>
<th>Time Horizon $T$</th>
<th>DMPC calls</th>
<th>Number of Branch Outages</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T = 1$</td>
<td>22</td>
<td>0</td>
</tr>
<tr>
<td>$T = 2$</td>
<td>32</td>
<td>2</td>
</tr>
<tr>
<td>$T = 3$</td>
<td>34</td>
<td>3</td>
</tr>
<tr>
<td>$T = 4$</td>
<td>50</td>
<td>13</td>
</tr>
</tbody>
</table>

Table 5.1: Number of branch outages for different time horizon $T$.

curve (Fig. 5.7(a)) or in the CBP curve (Fig. 5.7(b)). As we have already noticed in the centralized case, the total shedding cost decreases with the increase of the time horizon. This fact flows now directly into the distributed model, having there one advantage more: the CBP decreases considering bigger time horizons.

We did not consider the CBP in the centralized case on simulation over one day, since the day load shedding curve in Fig. 4.5 on page 27 is clear enough to observe the tendency. The CBP curve would increase for bigger time horizon because the peaks are increasing. In the distributed case it is the day curve (Fig. 5.6) which is the more confuse and which necessitates a clear plot which describes the ratio load shedding to demand. The stated CBP, as previously said, is prone to errors, but a decisive decrease of the probability in encountering a big blackout is noticed.

![Cumulative probability plots for DMPC.](image1)

(a) Cumulative probability for total shedding cost.

![Cumulative probability plots for DMPC.](image2)

(b) Cumulative blackout probability.

Figure 5.7: Cumulative probability plots for DMPC.
5.7.2 Communication Results

To gain some insight observation about the complex interaction and communication between the agents, I tried to observe the solution difference of the single agents. When an agent $M$ comes to the point in which it is demanded to chose an implementation, it has the possibility to chose his weighted optimization solution $\tilde{\delta}_M,0,i$ or the weighted solution of a neighbor $M_m \tilde{\delta}_{M_m,0,i}$. As described in Sect. 5.5.3 the decision is based on the biggest absolute value; if a neighbor offers a bigger deviation that its own, then the absolute difference $\Delta = |\tilde{\delta}_{M_m,0,i} - \tilde{\delta}_M,0,i|$ is logged, if the own solution is implemented a 0 is logged. Out of the data a density plot can be created (Fig. 5.8(b)) describing the dimension of the communication.

![Graphs showing cumulative blackout probability and density of solution difference](image)

(a) Cumulative blackout probability.  
(b) Density of absolute solution difference $\Delta$.

Figure 5.8: Comparison between two different control and solution ranges.

I simulated for two different ranges $R_c$ also with an increased range $R$ at a constant time horizon $T = 2$. In Fig. 5.8, I displayed, on one side, the CBP (Fig. 5.8(a)), analyzing the general cumulative blackout probability behavior with a different range and, on the other side, the density plots (Fig. 5.8(b)). As expected, by increasing the solution space and control space, the CBP curve decreases, meaning that there is a smaller possibility that bigger blackouts may occur. It is interesting to observe that on the other side on plot (Fig. 5.8(b)), the communication intensity increases, this is particularly to be noticed in the lower range between $\Delta = 0$ and $\Delta = 50$. It has to be added that the density plot has been cut at a height of 0.05, which has made an examination of the curve variation possible. The peak density 1 is at
$\Delta = 0$, meaning that no communication is existent, which implies that the own solution is the most likely to be implemented.

### 5.7.3 Long Term Simulations

To fortify the simulation done in the previous subsection, we still want to consider the long term analysis also carried out in the centralized approach chapter. The simulations were performed during approximatively one year following the year load curve as described in [10]. For the subsequent simulation we observe once more the CBP of the DMPC for different time horizons $T$. In fact as supposed in the one day simulations it can be shown that the curve is driven lower with a higher time horizon $T$. This fact is demonstrated in Fig. 5.9(a).

![Graphs of CBP and solution difference](image)

(a) CBP for different time horizon $T$ on the weakened RTS-96 for the DMPC.  
(b) Density of absolute solution difference $\Delta$ for different time horizon.

Figure 5.9: Long term simulation for different time horizon $T$.

With an increasing time horizon $T$, the probability for a certain blackout decreases. Moreover, we can observe that the augmenting of $T$ converges to a single curve, meaning that very long prediction horizons which come along with high computational efforts do not permit a continuously diminution of the CBP. The convergence curve occur out of the model limits and characteristics, which means that the shown plot is an indicative effect of the DMPC application to a system.

A fact that would have been difficult to analyze in the one day simulation because of the high degree of uncertainty is shown in Fig. 5.9(b). Once more, we consider
the communication between agents as cited in the Sect. 5.7.2. It is interesting to observe that the exchange of information decreases with an increasing time horizon. This behavior gives the possibility to increase the communication by enlarging the control and solution space and to move further down the convergence curve of the CBP as already described in Sect. 5.7.2. Therefore, we can conclude that by optimally designing the system parameters \( T, R_c, R \) in the distributed implementation of MPC we can approach, decreasing the CBP, to the theoretically global optimal curve obtained in the centralized implementation. For example, we can overlay the curve with the same prediction horizon \( T = 2 \) obtained for the centralized and for the distributed approach. This is shown in Fig. 5.10.

As we can see, the distributed MPC curve in red, with the variable parameters \( R = 2 \) and \( R_c = 1 \), is driven very close to the centralized MPC. It is to notice that for small load shed per demand the curves are almost identical, but they diverge for bigger blackouts. This means that regarding this model a centralized approach is, for identical time horizon \( T \), more efficient to avoid large-scaled cascading failures, thus a distributed approach offers a wider degree of freedom through modifying the model parameters \( (T, R_c, R) \). The system design is too complex to permit an analytical calculation of the optimal...
5.7. Results

system parameters, leaving the simulation procedure as unique possibility. Still, this very computationally expensive operation has been omitted in this report, basing the results on showing the parameter sensitivity on the system response and reliability.

5.7.4 Disturbance Effect

As it has also been considered in the centralized approach, we conclude the long term simulation analyzing the disturbance effect to the distributed MPC. The simulations are effectuated for two different $\sigma$ values: $\sigma = 0.01$ and $\sigma = 0.03$. Just like in the centralized Sect. 4.7.3, the model characteristics for each simulation are identical ($T = 2$, $R = 2$, $R_c = 1$).

The results are displayed in graph on Fig. 5.11.

![Figure 5.11: CBP for fixed time horizon $T = 2$ without noise in blue and with noise in red ($\sigma = 0.01$) and green in red ($\sigma = 0.03$).](image)

It is interesting to observe how strong the disturbance effect is on the distributed case, a very different effect, if we compare this to that of the centralized implementation. For larger $\sigma$ the curve is driven higher with a larger gap than observed for the centralized MPC in Fig. 4.8. This is to attribute to the fact that in a distributed
5.7.4. Disturbance Effect

implementation the single agents are more dependent on predictions. The actual optimization solution is based on a smaller range, which may be strongly coupled to the noisy local load forecast. In order to return to the original reliability, a correct prediction and noise suppression is hence even more important in the distributed MPC than in the centralized approach. This forces, in a future implementation, to choose a load prediction which is less noise sensitive than the actual one.
Chapter 6

Conclusion and Outlook

This chapter briefly recapitulates some of the most important conclusions of this master thesis and gives a short outlook about how the model and the control problem might be further developed.

6.1 Conclusion

In this master thesis, a modern automatic control technology, Model Predictive Control, is implemented in the widely used simulation test bed RTS-96. The linear MPC and a direct current network model to reduce computational effort and to obtain the biggest possible number of connected buses for best observing complex characteristics are chosen. To start with, the common centralized approach is adopted to analyze the general behavior of the automatic control. Some important findings are then applied to the distributed approach, in which communicating interacting agents try to solve the global optimization problem. The distributed approach not only enables to control wide electric power systems dividing the global problem into several subproblems solved by the agents, but also offers strong potential to prevent subsequent complex outages.

Two implementations forms of Model Predictive Control are investigated. The first approach solves the optimization problem centrally, which means that every parameter is directly observed and controlled. As the results show, on one side this characteristic helps to alleviate fast and efficiently the overload, but on the other side the cost can be decreased only by sacrificing reliability. The second approach which is also based on MPC but on a distributed implementation guarantees, as the simulation prove, that with an increasing time horizon, not only the cost can be reduced, but also the system reliability is improved. An overload is in this manner disengaged in a distributed way, in which interacting agents solve their own opti-
mization problems under strict constraints, collaborating with neighboring buses to find a general solution which is optimal for all components. The communication and interaction between agents generate a stirring effect which has a positive impact on the general system reliability. Contrarily to the centralized approach, the distributed level has the disadvantage to be prone to outages, since the interaction process can be completed unsuccessfully or the implementation parameters are uncoordinated. This is observed by increasing the time horizon because the optimization gets more and more complex.

Especially the distributed implementation has, as automatic control technology, strong potential. From the electrical system point of view, through a distributed implementation, new electric networks with their own control agents can be simple added to the existing system. Overloads are alleviated by interacting and communicating subnetworks maintaining the reliability close to a centralized approach.

6.2 Outlook

Principally, the proposed system is kept as simple as possible such that also extensive behavior could still be observed; to fortify the observation, the model must be amplified almost in every direction increasing the degree of complexity. Some of the possible extensions are here listed:

- More tests over larger networked systems need to be performed to precisely analyze cascading effects and complex characteristics. The effect of enlarging the system renders the model rapidly complex making it difficult to observe interacting activities which cause intricate phenomena.

- Further analysis with hybrid system can be applied. It has only be considered the outage of a transmission line, which is ideally amplified considering also outages of generator and load units.

- Along with the last point, also the predictions could be fortified with probabilistic predictions that enable to forecast outages and providing the controller with useful information about system state evolutions.

- The objective function could be enlarged considering the time factor of a load shedding. An idea could be to weight the load in the objective function with a $\Delta_{t,\text{shed}}$, the time during which this load has already been in the shedding state. Or the objective function could directly contain the information about the load shedding per time surface obtained by present, past and future load shedding.
• More complex communication algorithms can be integrated to observe if the reliability can be driven down globally. Various publications (for example in [13]) prove that through information exchange a strong ameliorating potential is available.

• For an intensive reliability analysis under the load disturbance effect, a better load prediction algorithm should be implemented, trying to damp the noise consequences and to drive the reliability back to the original state.
Appendix A

Calculations

In this Appendix chapter the general used calculations are treated, defining first the sensitivity factors and secondly the cumulative distribution.

A.1 Sensitivity factors

The linear sensitivity factors $a_{i,n}$ give information about how the flow over a transmission line $i$ changes when active power injection at the node $n$ changes. The detailed calculations are given in [19]. For the sake of completeness I give an overview of the most important formulas to calculate the sensitivity factors.

Starting with the matrix formulation of DC power flow in Sect. 3.3, the sensitivity factor for a shift of 1 unit at bus $n$ can be derived from equation:

$$\Delta \Theta = (B')^{-1} \Delta P$$

when setting an element $n$ of the matrix $\Delta P$ to +1, the reference or slack element to -1 and all other elements to 0. The linear sensitivity factor for line $i$ having reactance $x_i$, with respect to a change in injected power at bus $n$, is thus

$$a_{i,n} = \frac{1}{x_i} \left( \frac{d\Theta_j}{dP_n} - \frac{d\Theta_k}{dP_n} \right)$$

where

$$\frac{d\Theta_j}{dP_n} = n^{th} \text{ element from the } \Delta \Theta \text{ vector}$$

$$\frac{d\Theta_k}{dP_n} = n^{th} \text{ element from the } \Delta \Theta \text{ vector}$$
A.2 Cumulative Distribution

In various diagrams I chose to show the results in a concise cumulative distribution plot. The cumulative distribution is a well known distribution form in the probability theory. As stated in many text books we can describe the probability distribution of a real-valued random variable $X$ as following:

$$x \rightarrow F_X(x) = P(X \leq x) \quad (A.3)$$

where $x$ stays for a real number. The right hand side represents the probability that the random variable $X$ takes a value less than or equal to $x$. The probability that $X$ lies in the interval $(a, b]$ is therefore $F(b) - F(a)$ if $a < b$. The cumulative distribution function $F$ possess some important properties: every cumulative distribution function $F$ is monotone increasing and right-continuous. Furthermore, we have:

$$\lim_{x \rightarrow -\infty} F(x) = 0 \quad (A.4)$$
$$\lim_{x \rightarrow \infty} F(x) = 1 \quad (A.5)$$

Every function with these four proprieties is a cumulative distribution function. However, in is sometimes useful to study the opposite and ask how often the random variable is above a particular level. This is called the complementary cumulative distribution function, defined as

$$F_c(x) = P(X > x) = 1 - F(x) \quad (A.6)$$

the cumulative blackout probability (CBP) is based on the complementary cumulative distribution function.
Appendix B

Reliability Test System -1996

As the topology has already been described in Chap. 3 and all data are available in [10] we restrict the description in this Appendix chapter to the weakened system, defining the modified values.

B.1 Weakened System

To best describe the dynamics of the system I chose a weakened system, which has the following modified short time emergency ratings (STER):

<table>
<thead>
<tr>
<th>Branch ID</th>
<th>Old STER</th>
<th>Modified STER</th>
</tr>
</thead>
<tbody>
<tr>
<td>A16</td>
<td>600</td>
<td>150</td>
</tr>
<tr>
<td>A20</td>
<td>625</td>
<td>150</td>
</tr>
</tbody>
</table>

Table B.1: Modified short time emergency rating (STER).

In Fig. 3.1 on page 11 the branch ID A16 and A20 are signed as 16 and 20. Furthermore the load and generation capacity has been increased by a factor of 1.5 to guarantee a high workload on the transmission lines.
Bibliography


