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Comparison of Different Redispatch Optimization Strategies

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Comparison of Different Redispatch Optimization Strategies

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I Abstract

In the recent years, line congestions in the electric transmission networks occur quite frequently due to the power grids were not originally designed for the current amount of energy and its strong fluctuation. Furthermore, the increasing utilization of renewable distributed energy sources, growth of the network complexity, reduction of the conventional power plant utilization, forecast errors and strong electricity market competition frequently bring the power grids to their transmission limits as well. Therefore, the risk of congestions has permanently increased, especially in central Europe.

If a line congestion occurs in the electric network, the transmission system operator has to apply a suitable remedial action to overcome the problem as fast as possible, e.g by utilization of redispatch, which is very common in Germany. However, this measure can cause high costs for the transmission network operators. For this reason, the realization of an economically efficient and optimal redispatching has become very important issue in the power system operation.

The main goal of this work is a consideration and development of various possibilities and methods for realization of a technically sound and cost-efficient redispatch in case of network congestions. Therefore, different numerical and metaheuristic optimization techniques are implemented, compared with respect to their complexity, efficiency, reliability, simulation time etc. and verified through a small test grid and simplified ENTSO-E network model.

Furthermore, it is shown which technical and economic aspects of redispatching have a major influence on its realization and should always be taken into account or can be neglected while solving the redispatch optimization problem. Here, different approaches of the network sensitivity analysis are evaluated and compared as well.

Finally, the transmission network operators can use the knowledge and results of this work to improve the current redispatch realization in their power grids, and thus to reduce the redispatch costs, which are especially high in Germany.

II Kurzfassung

In den letzten Jahren hat die Häufigkeit des Auftretens von Engpässen in den elektrischen Übertragungsnetzen stark zugenommen, weil die Stromnetze ursprünglich für die aktuelle Energiemenge und deren starke Schwankung nicht ausgelegt sind. Darüber hinaus bringen die weiter steigende Nutzung der erneuerbaren dezentralen Energiequellen, die zunehmende Netzkomplexität, die Abschaltung konventioneller Kraftwerke, Prognosefehler und der starke Wettbewerb auf dem Strommarkt die elektrischen Netze immer öfter an ihre Übertragungsgrenzen. Daher ist die Gefahr von Engpässen permanent gestiegen, insbesondere in Mitteleuropa.

Wenn ein Engpass im Stromnetz entstanden ist, sind die Übertragungsnetzbetreiber verpflichtet, eine geeignete Abhilfemaßnahme so schnell wie möglich anzuwenden, um ihn zu beseitigen, z. B. durch den deutschlandweit verbreiteten Redispatch. Allerdings kann diese Gegenmaßnahme hohe Kosten für die Übertragungsnetzbetreiber verursachen, die zum Schluss die Stromverbraucher zahlen müssen. Deswegen ist die Realisierung eines kosten- und technisch effizienten Redispatches ein sehr wichtiges Thema des Netzbetriebs geworden.

Daher ist das Hauptziel dieser Arbeit, unterschiedliche Möglichkeiten und Ansätze für eine kostengünstige Redispatchumsetzung bei Entstehung der Engpässe zu entwickeln. Dafür werden verschiedene numerische und metaheuristische Optimierungsmethoden hinsichtlich ihrer Komplexität, Effizienz, Verlässlichkeit, Detaillierung und Rechenzeit verglichen und durch ein kleines Netzmodell sowie durch ein vereinfachtes ENTSO-E-Netzmodell verifiziert.

Schließlich werden die Übertragungsnetzbetreiber durch die Erkenntnisse in dieser Arbeit in die Lage versetzt, ihre Stromnetze effizienter zu betreiben, in dem der Redispatchprozess verbessert wird. Dabei werden die hohen Redispatchkosten, insbesondere in Deutschland, deutlich gesenkt.

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VI List of Symbols

Notation

$\boldsymbol{A}$	matrix
$\boldsymbol{a}$	vector
a, A	scalar
$\underline{a}$, $\underline{A}$, $\underline{\boldsymbol{a}}$, $\underline{\boldsymbol{A}}$	complex value

Latin symbols

$\boldsymbol{A}$	constraint system
a	pivot element
b	constraint restrictions
d	binary value, distance, parameter of the GA
C	penalty coefficient
c	acceleration coefficients, costs, chromosome, objective function
F	feasible area
f	factor, function
G	Gaussian, number of power plants
h	h-function
I	current, identity matrix
J	feasible solution, Jacobian
K	topological matrix
L	route length
P	active power
p	position, probability
penalty	penalty
Q	reactive power, optional weighting
q	parameter of solution selection
R	route
S	apparent power
s	shape variable
sd	binary variable for shut-down
su	binary variable for start-up
T	simplex tableau

t	time
U	voltage
U	unit vector
V	probabilistic prospect
v	value function, vareance, velocity
w	inertia weight factor
x	searched variable
Y	admittance

Greek symbols

α	user-defined constant
β	user-defined constant, random number
γ	weighting parameter
Δ	change
$\Delta\tau$	pheromone quantity
δ	phase angle
η	heuristic value
λ	constant, heat-loss coefficient, user-defined constant
μ	mean
ξ	factor
ρ	pheromone evaporation
σ	sensitivity matrix coefficient, standard deviation of the Gaussian distribution function, variance
τ	pheromone trail
ω	weighting vector

Indexes

best	best
c	centroid, column number
cong	congestion
contr	contraction
crp	crossover point
dir	direct
e	expansion

f	‘father’
fo	forced outage
h	highest
hr	heat rate
incr	increase
indr	indirect
K	node
k	exponent, number of solutions
G	generator
gl	global best position
L	line, load
lb	current best position
l	level number, lowest
LCOE	levelized costs of electricity
m	‘mother’, number of constraints
max	maximum
min	minimum
mut	mutation
n	number of ants, best solutions, chromosomes, function variables
new	new
offspr	offspring
old	old
RP+, RP-	positive and negative redispatch potential
r	reflection, row number
ramp	ramping
red	reduction
s	shape
sd	shut-down
start	smallest value
su	start-up
T	terminal

Superscript indices

*	complex conjugated
T	transposed

VII List of abbreviations

ACO	Ant Colony Optimization
ACOR-PT	Ant Colony Optimization with the Prospect Theory
AC-PTDF	AC Power Transfer Distribution Factors
CM	Congestion Management
ENTSO-E	European Network of Transmission System Operator
GA	Genetic Algorithm
LCOE	Levelized Costs of Electricity
LP	Linear Programming
MF	Mapping Function
MVMO	Mean Variance Mapping Optimization
PDF	Probability Density Function
PFD	Power Flow Decomposition method
PPCC	Power Plant Cycling Costs
PPSDC	Power Plant Shut-Down Costs
PSO	Particle Swarm Optimization
PT	Prospect Theory
RES	Renewable Energy Sources
SS	Sequential Simplex
TSO	Transmission System Operator
TSP	Traveling Salesman Problem

1 Introduction

1.1 Motivation

Nowadays, the European electric network very often works at its transmission limits because of a massive growth of the power system operation complexity and transmission distances since the end of the nineties, which is caused by the enormous increase of the European electricity market. These strong changes in the electricity market have occurred because of the market liberalization, installation of a new European cross-border market and growing utilization of the renewables. Hence, a limitation of the transmission capacity in the European countries, the permanent increase of the electricity consumption, some forecast errors and delays in the network expansion can lead to different emergencies such as network congestions. Therefore, in the recent years, line congestions occur quite frequently in the European electric transmission network. [1], [2], [3]

In case of a line congestion, the transmission system operators must apply a suitable remedial measure as soon as possible. One of the methods to avoid or remedy line congestions is redispatch. It is often used by system operators, especially in central Europe. Today, remedial actions of more than several thousand megawatts are a daily routine. Furthermore, there is an increasing risk of complete exhaustion of the redispatch potentials leading to emergency situations. Therefore, the realization of an efficient redispatch has become an important topic in the system operation.

Redispatching is a market-related remedial measure. Hence, for an optimal redispatch not only its technical but also economic aspects, e.g. the power flow equations, network sensitivity analysis, power plant potentials, costs for the redispatch realization, start-up and shut-down costs of the power plants, should be considered.

1.2 Objectives

In this work, different possibilities and approaches of the redispatch optimization are introduced and verified in test network models. For each developed optimization method, a suitable formulation of the considered optimization problem is proposed. Here, various technical and economic aspects of the redispatch realization are taken into account. It is determined, which components have a strong influence on the redispatching and should be considered in the optimization problem. Therefore, the introduced optimization problem consists of different linear and non-linear equations, which make an implementation of the optimization methods complicated.

Furthermore, the simulation results of the developed optimization approaches for an efficient redispatch realization are compared with regard to the complexity, detailing, reliability, efficiency and computation time.

Finally, the knowledge of this work can help the transmission network operators to realize the redispatching, resp. to operate their power grids, more efficient. Hence, the costs for the redispatch can be significantly reduced, which reduces electricity prices for the end customers.

1.3 Structure of this work

To achieve the above-described objectives, this work is structured as follows.

In chapter 2, processes of congestion management are described in detail. This chapter gives an overview of a definition of congestion management, its regulations in the European electricity market and the existing congestion management methods.

In chapter 3, different technical and economic aspects of the redispatch realization are described in detail. Moreover, the *Power Flow Decomposition* and two *AC Power Transfer Distribution Factors* methods for the calculation of the *network sensitivity analysis* are compared and tested in some standard IEEE and simplified ENTSO-E power grid models.

In chapter 4, fundamental knowledge of the optimization methods, linear programming and metaheuristic optimization techniques are provided. Furthermore, the optimization algorithms, which are used in this work, namely *simplex*, *genetic algorithm*, *Mean Variance Mapping Optimization*, *Particle Swarm Optimization*, *Ant Colony Optimization*, and different methods for the *constraint handling* are described in detail. In addition, the performance of the utilized optimization methodologies is introduced.

In chapter 5, the efficiency, accuracy and possible benefits of the previously introduced metaheuristic algorithms for solving the non-linear redispatch optimization problem are verified by using different electric network models.

Finally, this work ends with a summary and outlook for a possible future improvement of the redispatch optimization.

2 Congestion management

Since the end of the nineties, there is a drastic growth of the European electricity market because of the high intensity of market liberalization, newly installed European cross-border markets and growing use of the renewables. For this reason, the power system operation complexity and transmission distances rapidly increase as well. The annual load raise, limitation of the transmission capacity on country borders and general transmission capacity of the European countries as well as delays in the power grid expansion can lead to emergency situations of network transmission facilities in different places. Consequently, the risk of network congestions is permanently growing [1]. In addition, in the future a secure network operation will be more important than a cost reduction for electricity consumers, because dependence of the industry, public institutions and other consumers on the secure network operation has significantly increased due to the trend to automation and computerization [2]. Therefore, the network congestion management has become a very important issue for the transmission network operation.

2.1 Congestions in the power systems

According to the Regulation No 714/2009 of the European Parliament and of the Council of 13 July 2009 on conditions for an access to network for cross-border exchanges in electricity, a network congestion means „*a situation, in which an interconnection linking national transmission networks, cannot accommodate all physical flows resulting from international trade requested by market participants, because of a lack of capacity of the interconnectors and/or the national transmission systems concerned*“. Therefore, the main reason why congestions occur in the electric networks is a lack of the transmission capacity [3].

Based on the Continental Europe Operation Handbook of the European Network of the Transmission System Operators (ENTSO-E), the power system, which consists of n components, has to stay stable after a contingency or operational trip of electrical equipment even with n-1 components. Furthermore, the thermal limits of power lines, which are dependent on the transmission capacity as well as the voltage and frequency limits, must not be exceeded. If the (n-1)-criterion is violated, a congestion occurs in an electric network. In this case, the transmission system operators (TSOs) have to apply a suitable measure to remedy it fast, secure and cost-efficient. [4], [5], [6]

2.2 Definition of congestion management

In accordance with the German Federal Network Agency the congestion management (CM) must include all possible actions in the power grids, which can be applied by the network operator to avoid or remedy congestions in the power system [7].

2.2.1 Regulation of the congestion management in Europa

Based on the Regulation No 714/2009 of the European Parliament and of the Council of 13 July 2009, the CM must include the following main principles [3], [8]:

- secure operation of the power grids must be kept
- CM should be economically efficient
- CM should be based on an open competition
- CM should be non-discriminatory and transparent for all participants
- the available transmission capacity should be utilized completely
- revenues from CM should be used by some rules

2.2.2 Regulation of the congestion management in Germany

First, according to § 13 EnWG of the Federal Ministry for Economic Affairs and Energy in Germany [9], the TSOs should attempt to prevent network congestions in their own networks and on the interconnections with the neighboring power grids using network-related remedial actions (e.g. topological changes). If these non-costly measures did not help, in the next step, the operating reserve of the electric network can be used to prevent congestions. Additionally, the network operators can conclude agreements with the power plant operators and/or electricity consumers for connection or disconnection of the generation plants or loads. For this, the affected participants get revenues from them. This market-related measure can balance the network load without any forced curtailments. The remaining transmission capacity must be spread non-discriminatory, market-oriented and transparent. The additional revenues from these procedures must be invested in the network expansion.

Only if this did not help, the access to the electric network can be denied for the power plant operators taking into account the priority of the particular power plants (§7 Kraft-NAV [10]). Moreover, the load curtailment can be forced by the system operators. In these emergency cases, the affected participants get no revenues from them.

Figure 2.1 shows a simplified representation of the CM as described above based on [11].

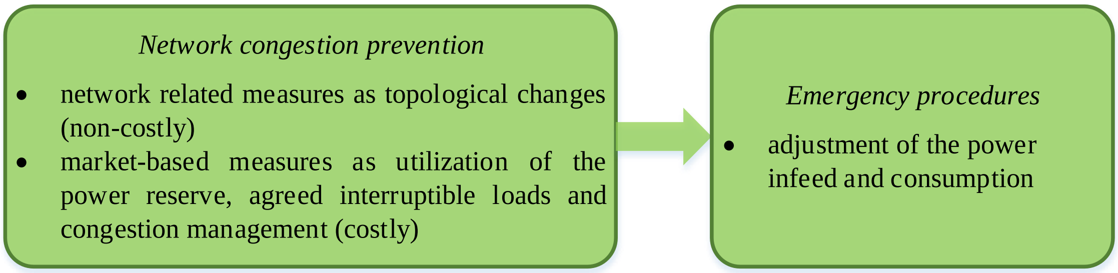

Figure 2.1 Simplified representation of the CM [11]

2.3 Congestion management methods

The most discussed classification of the congestion management methods consists of two big groups:

- congestion prevention or remedy (short-term CM)
- transmission capacity allocation (long-term CM)

Each of these groups includes many different techniques of the CM, which are described below in this chapter and summarized in Figure 2.2.

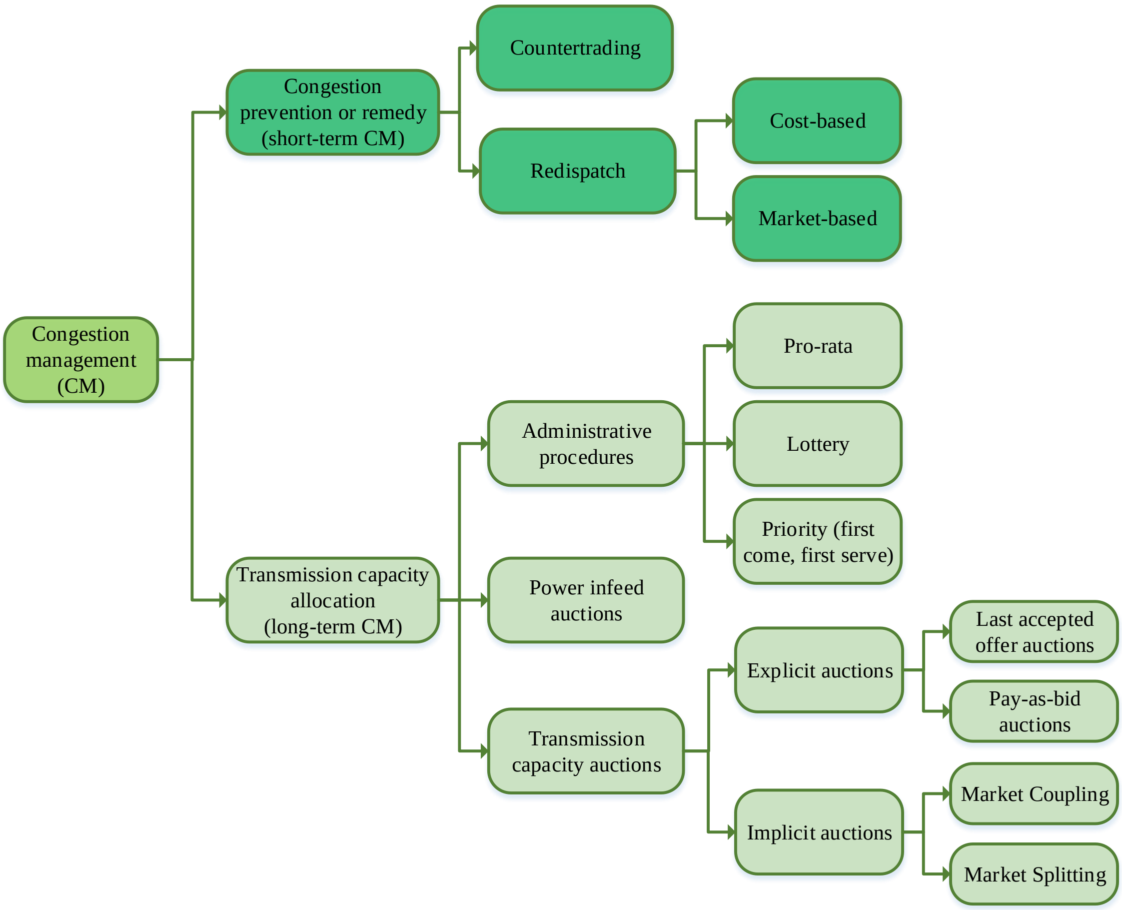

Figure 2.2 Overview of the congestion management classification [8], [12], [13], [14]

2.3.1 Congestion prevention or remedy (short-term CM)

The main purpose of the congestion prevention/remedy is to avoid/remedy network congestions, which randomly or temporarily occur in the electric networks in the short term. But the most important point here is to keep the power system stability and ensure the secure network operation. Therefore, this type of the CM must be realized very quickly to change the network state rapidly and, in this way, to avoid the power grid instability, resp. a blackout. Due to this reason, the chosen CM methods must be flexible enough to relieve the power flow on the congested lines as fast as possible. [12]

There are three methods for network congestion prevention or remedy in the short term: *redispatch*, *countertrading* and *load management*. These methods are described in detail below.

2.3.1.1 Redispatch (power generation management)

Redispatching (shortly *redispatch*) is an often applied preventive/curative measure to avoid/remedy network congestions in the short term. By the redispatch the power generation is reduced at the long side of the congested line and increased at its short side. The TSO, which is responsible for the network area where the congestion occurs in a short time or has been occurred recently, must adapt the already applied power plant resource scheduling to reduce the power flow over the congested line and, in this way, keep the power network stable. Therefore, the redispatch is an administrative procedure, by which the TSOs decide which power plants must change their power infeed [15], [16].

After applying the power plant resource scheduling the current power flow, resp. congestion flow, is exactly determined. If a line congestion occurs shortly, the most suitable power plants for a redispatch realization has to be selected by the responsible TSO. Then the affected power plants must adjust their active power infeed. The most important point here is that the active power balance in the electric network must be kept at any time [17]. Consequently, the electricity consumers are not affected by this remedial measure.

First, by redispatching, the pricing on the electricity market does not change because the TSO contacts all affected power plants directly. Nevertheless, the redispatch participants are expecting a compensation. Therefore, the total costs, which arise thereby, is paid by the network utilization fees. [16]

There are two types of the redispatching in terms of the financial implementation: *cost-based* and *market-based.*

A *cost-based* redispatch is based on the actual cost arising from its realization. Here, the power plant operators get a compensation for increasing the power generation during the redispatch realization. On the other hand, the operators, whose power plants reduced the power generation, must reimburse the saved costs to the TSO because their customers paid them for the electricity, which they did not actually provide during this time. In fact, this electricity was generated by the power plants, which must increase their active power generation during the redispatch. In this way, the TSO reduces the costs for the redispatch realization. [12]

A *market-based* redispatch is a redispatch power auction for avoiding an impending line congestion. Based on the power plant resource scheduling, power generation and load forecasts, the TSOs can approximately evaluate the network power flow for the next day.

If the congestions are foreseeable, the determined redispatch power is tendered on a special platform. Here, the power plant operators can offer to increase or reduce their active power output. After that the TSOs make a *merit order* from all offers and take the most suitable power plants for the redispatch realization. This method is non-discriminatory and transparent for all auction participants. However, there is a risk that the power plant operators can get a monopoly over the redispatch power because the redispatch market is very small. Furthermore, line congestions usually occur at the same places in the power grids, which leads to a utilization of the same power plants and strengthening of the monopoly on the redispatch market as well. [12]

2.3.1.2 Countertrading

A *countertrading* or *counter-trade* is a preventive/curative measure to avoid/remedy network congestions in the short term and is based on the *redispatching*. Actually, the *countertrading* is a *redispatch* with own *merit order* for the power plant selection [16]. It can be used not only between different trade areas as by the explicit and implicit auctions but also within only one trade and price area [5], [12].

Here, the power plants in the export area have to reduce their power generation. However, they have already sold a certain amount of the active power on the electricity exchange, which they do not produce anymore. Therefore, they must buy back this electricity surplus from the TSO for a price, which is smaller than the market price. Furthermore, the power plants in the import area need to increase their power generation. For this, the TSO pays them more than the market price. Therefore, the TSO bears losses for the realization of the *countertrading*. [18]

In addition, the TSO has no influence on the selection of the participating power plants, i.e. power plants are only selected by the costs for the power generation. For this reason, the physical effect of the *countertrading* on the power system is not completely predictable.

2.3.2 Transmission capacity allocation (long-term CM)

The main goal of the *transmission capacity allocation* is to avoid network congestions, which permanently occur in the power grid. In the European Union such congestions have become a major problem for a long time, especially on the cross-border interconnections [12].

There are three main groups of methods for the transmission capacity allocation: *administrative procedures*, *market-based* and *power infeed auctions*. These methods are described in detail below.

2.3.2.1 Transmission capacity auctions (market-based)

The biggest and most used group of methods is based on a market model and consists of the so-called *transmission capacity auctions*. These methods are economically efficient, non-discriminatory and transparent. In addition, they ensure an open market competition in this field.

Here the network transmission capacity is auctioned by the electricity market to guarantee the maximum balance between the supply and demand. Therefore, the available transmission capacity is completely exhausted, which is important to avoid network congestions. These transmission capacity auctions include mostly *explicit* and *implicit auctions* [12].

Explicit auctions

Explicit auctions are preventive measures to avoid a network congestion [5]. Here, the network transmission capacity is auctioned separately from the electricity market. At the beginning of an explicit auction the available transmission capacity is disclosed by its owners (TSOs, resp. auction office [19]). Then the interested participants of the auction (e.g. power plants, electricity traders etc.) place bids. However, the electricity price is not known exactly at that time and cannot be considered in the explicit auction. Therefore, the bidders can make their offers based only on own experience and market observation. After that the submitted bids are sorted in a descending order and the available network transmission capacity is spread between the highest of them until it is exhausted [20].

There are various types of explicit auctions. By the so-called *last accepted offer auctions*, which are very common, all auction participants pay only the amount of the last accepted bid [20]. By *pay-as-bid auctions* every bidder pays the own proposed price.

In addition, the explicit auctions take place within different time ranges such as a year, month or day.

The explicit auctions can be easily implemented, which makes them very attractive for the network transmission capacity market. However, they cannot guarantee an optimal utilization of the congested cross-border interconnections due to separation of the transmission capacity from the electricity market.

Implicit auctions

As well as the explicit auctions, *implicit auctions* are preventive measures to avoid a network congestion. However, by the implicit auctions the network transmission capacity is traded coupled with the electricity market. This means that the transmission capacity cannot be auctioned decoupled from the electricity trading. The electricity exchange together with the TSOs takes care of the coordination between the electricity trading and available network transmission capacity [12]. Therefore, the implicit auction participants can focus only on the electricity trading market.

Basically, there are two main types of the implicit auctions: *Market Coupling* and *Market Splitting*. By the *Market Coupling* several electricity exchanges with many different trade areas and price ranges are involved in the coordination between the electricity trading and available transmission capacity [12], [16]. By the *Market Splitting*, on the contrary, only one electricity exchange takes care of this coordination.

By the *Market Coupling* the participants often establish a joint venture, the so-called auction office, to organize a successful cooperation between them. After closure of trading on the day-ahead market all order information as well as the available transmission capacity are provided to an auction office [21]. Based on the available information, the auction office determines the optimal power flow between the market areas and price independent buy and sell orders to ensure it [12].

Because there is only one electricity exchange by the *Market Splitting*, there is no need to establish an auction office. In all other respects, its working concept is very similar to the *Market Coupling*.

In opposite to the explicit auctions, the implicit auctions are realized only in the short term, resp. on a day-ahead basis, because the actual information about the electricity trading can be only provided in the short term as well [21].

Furthermore, the implicit auctions can be combined with the explicit auctions to ensure the transmission rights for the auction participants for a longer period of time. First, the physical transmission rights are auctioned explicitly in the middle or long term. Then the auction office allocates the remaining transmission capacity implicitly on the day-ahead basis. Furthermore, the already acquired transmission rights can be restricted by the network instability risk. [12]

An optimal case of the *Market Splitting* from an economic point of view is *Nodal Pricing*. Here, every power plant or a big load is a node, a small submarket, with an own trade area and price [16]. However, due to many nodes in the real electric networks such as the European power grid, it is very complicated to utilize the *Nodal Pricing* method practically.

2.3.2.2 Administrative procedures

Administrative procedures used to be very important for the transmission capacity allocation on the power grid interconnectors in Europe before 01 July 2004, till the regulation on the cross-border trade for the European electricity market came into force [20]. The TSOs used to be completely responsible for the capacity allocation on the interconnectors and had plenty of scope compared to the market-based capacity allocation model.

There are three most important methods of the administrative procedures: so-called *lottery, priority* and *pro-rata* methods [12].

By the *lottery* method the available transmission capacity is randomly allocated between the participants of the electricity market. This method is non-discriminatory and transparent. However, it is not an economically optimal solution.

By the *priority* method (*first come, first serve*) the transmission capacity is allocated in order of the received requests from the electricity market participants until the available capacity is completely exhausted [13]. This method is easy to realize, but it can be discriminatory for the participants and is not always economically efficient.

By the *pro-rata* method the available transmission capacity is allocated proportional between all interested electricity market participants [13]. Moreover, the number of the requests, which are received from one participant, is also considered and affects the ratio of the allocated capacity. This method is non-discriminatory and easy to realize, however, not always economically optimal.

Therefore, all *administrative procedures* can be easily and quickly realized. However, they can be more discriminatory, not transparent and not economically efficient enough compared to the *market-based* methods.

2.3.2.3 Power infeed auctions

In this approach, the power plants are allowed to feed the active power in a congested network area only if they have bought the infeed rights at the explicit auction in advance. By the *power infeed auctions* only a limited number of the infeed rights can be auctioned to ensure the secure network operation.

Basically, this concept is easy to implement for the network areas with permanent congestions. However, the electricity price in these areas rises extremely due to the limitation of the infeed rights. Consequently, the power infeed auctions are not currently used in the European area.

3 Technical and economic aspects of redispatch

To remedy network congestions in the electric networks, *redispatching* is frequently utilized by the transmission system operators. As already described in chapter 2, the *redispatch* is a market-related remedial measure and means a controlled change of the active power plant generation capacity in order to remedy line congestions. To realize an efficient redispatch, it is important to consider different kinds of its technical and economic aspects.

3.1 Technical aspects of redispatch

First of all, for a redispatch realization the suitable power plants, which have a high impact on the power flow through the congested line, need to be found. For this reason, network sensitivity analysis has to be done. [4], [17], [15], [22]

3.1.1 Redispatch principle

If a power line in the electric network is congested, the power generation on its long side must be reduced, i.e. this is a power surplus area. At the same time, the power generation on the short side of this line must be increased by the same amount, i.e. this is a power deficit area. This process of the redispatching is shown in Figure 3.1.

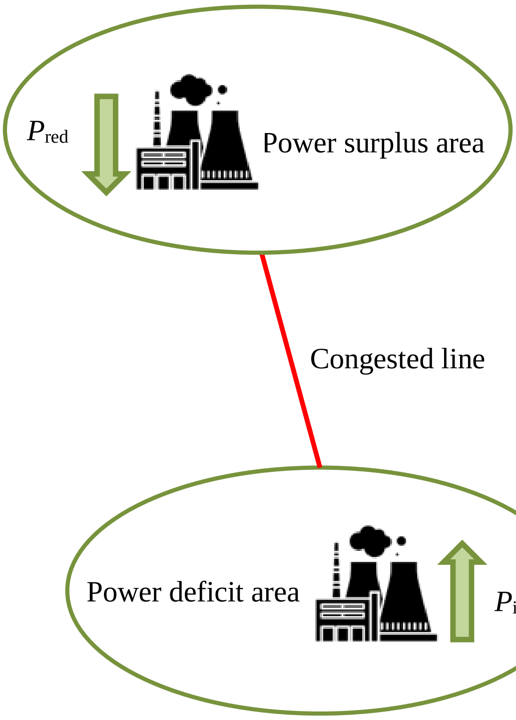

Figure 3.1 Redispatch principle

Therefore, the active power system balance must be kept at any time. Hence, the amount of the power generation reduction P_{red} on the long side of the congested line must be equivalent to the amount of the power increase P_{incr} on the other side of this power line [4], [17], [15], [22]:

$$P_{\text{red}} + P_{\text{incr}} = 0 \tag{3.1}$$

To realize an effective redispatch the most suitable power plants must be chosen. Therefore, the transmission network operators usually use different methods for the *network sensitivity analysis*.

The amount of the nodal power changes of the chosen power plants can be determined using the active power amount P_{cong}, to which the active power on the line should be reduced in order to remedy the line congestion, and the sensitivity matrix coefficients σ [4], [17], [15], [23]:

$$P_{\text{red}}\sigma_{\text{red}} + P_{\text{incr}}\sigma_{\text{incr}} = P_{\text{cong}} \tag{3.2}$$

where σ_{red}, σ_{incr} are the sensitivity matrix coefficients, which describe the nodes with the strongest impact on the congested line. In addition, the sign of these coefficients shows a relieving or burdening effect of the nodal active power change. σ_{incr} for the power increase must be a positive value and σ_{red} for the power reduction – a negative.

Therefore, based on equations (3.1) and (3.2), the relationship between the nodal active power changes of one generator pair, sensitivity matrix coefficients and needed active power change on the congested line can be formulated as follows:

$$\begin{bmatrix} \sigma_{\text{red}} & \sigma_{\text{incr}} \\ 1 & 1 \end{bmatrix} \begin{bmatrix} P_{\text{red}} \\ P_{\text{incr}} \end{bmatrix} = \begin{bmatrix} P_{\text{cong}} \\ 0 \end{bmatrix} \tag{3.3}$$

with

$$P_{\text{incr}} = -P_{\text{red}} \tag{3.4}$$

Based on equation (3.3) and (3.4), the needed nodal active power injection for the remedy of the line congestion can be easily found as shown in (3.5):

$$P_{\text{incr}} = \frac{P_{\text{cong}}}{\sigma_{\text{incr}} - \sigma_{\text{red}}} \tag{3.5}$$

3.1.2 Sensitivity analysis

The sensitivity of a nodal active power injection for a power flow change on a line depends on several major effects, e.g. switching states, load and active power generation pattern, but is influenced as well by transformer tapping, nodal reactive powers, shunt elements, etc. The *Power Flow Decomposition method* (PFD) is the only technical sound method, which is able to consider all of the mentioned effects. This approach allows to linearize the quadratic power flow equations, in such way that the system keeps its original operation point. Furthermore, it does not need any special slack bus treatment. [17]

Based on the power flow calculation, the nodal currents $\underline{\boldsymbol{i}}_{\text{K}}$ can be found as shown below:

$$\underline{\boldsymbol{i}}_{\text{K}} = \underline{\boldsymbol{Y}}_{\text{KK}} \underline{\boldsymbol{u}}_{\text{K}} \tag{3.6}$$

where $\underline{\boldsymbol{Y}}_{\mathrm{KK}}$ is the bus admittance matrix and $\underline{\boldsymbol{u}}_{\mathrm{K}}$ is the nodal voltage vector.

On the other hand, the nodal currents $\underline{\boldsymbol{i}}_{\mathrm{K}}$ can be represented as a sum of the load $\underline{\boldsymbol{i}}_{\mathrm{K,L}}$ and generator $\underline{\boldsymbol{i}}_{\mathrm{K,G}}$ currents [15], [24], [25], [26], [27]:

$$\begin{gathered}\underline{\boldsymbol{i}}_{\mathrm{K}} = \underline{\boldsymbol{Y}}_{\mathrm{KK}}\underline{\boldsymbol{u}}_{\mathrm{K}} \\ \text{or} \\ \underline{\boldsymbol{i}}_{\mathrm{K.L}} + \underline{\boldsymbol{i}}_{\mathrm{K,G}} = \underline{\boldsymbol{Y}}_{\mathrm{K,L}}\underline{\boldsymbol{u}}_{\mathrm{K}} + \underline{\boldsymbol{i}}_{\mathrm{K,G}}\end{gathered} \tag{3.7}$$

where $\underline{\boldsymbol{Y}}_{\mathrm{K.L}}$ is the nodal admittance matrix for the loads.

Based on equation (3.7), the generator currents $\underline{\boldsymbol{i}}_{\mathrm{K,G}}$ can be determined as follows:

$$(\underline{\boldsymbol{Y}}_{\mathrm{KK}} - \underline{\boldsymbol{Y}}_{\mathrm{K,L}})\underline{\boldsymbol{u}}_{\mathrm{K}} = \underline{\boldsymbol{i}}_{\mathrm{K,G}} \tag{3.8}$$

Therefore, the new nodal admittance matrix $\underline{\boldsymbol{Y}}_{\mathrm{KK,L}}$, which is based on the generator currents, can be calculated by:

$$\underline{\boldsymbol{Y}}_{\mathrm{KK,L}} = \underline{\boldsymbol{Y}}_{\mathrm{KK}} - \underline{\boldsymbol{Y}}_{\mathrm{K,L}} \tag{3.9}$$

In addition, the nodal apparent power flow $\underline{\boldsymbol{s}}_{\mathrm{K}}$ can be established by:

$$\underline{\boldsymbol{s}}_{\mathrm{K}} = 3\underline{\boldsymbol{U}}_{\mathrm{K}}\underline{\boldsymbol{i}}_{\mathrm{K}}^{*} = 3\underline{\boldsymbol{U}}_{\mathrm{K}}\underline{\boldsymbol{Y}}_{\mathrm{KK}}^{*}\underline{\boldsymbol{u}}_{\mathrm{K}}^{*} \tag{3.10}$$

Due to the fact that the nodal admittance matrix is constant and the power changes are only depending on derivations of the node voltage vector, the changes in the active $\Delta\boldsymbol{p}_{\mathrm{K,G}}$ and reactive $\Delta\boldsymbol{q}_{\mathrm{K,G}}$ powers can be calculated by the nodal Jacobian matrix $\boldsymbol{J}_{\mathrm{KK,L}}$, which is based on the generator currents, using the Taylor series expansion as follows [2.3]:

$$\begin{bmatrix}\Delta\boldsymbol{p}_{\mathrm{K,G}} \\ \Delta\boldsymbol{q}_{\mathrm{K,G}}\end{bmatrix} = \boldsymbol{J}_{\mathrm{KK,L}}\begin{bmatrix}\Delta\boldsymbol{\delta}_{\mathrm{K}} \\ \Delta\boldsymbol{u}_{\mathrm{K}}\end{bmatrix} \tag{3.11}$$

Therefore, the changes of the node voltages $\Delta\boldsymbol{u}_{\mathrm{K}}$ and voltage angles $\Delta\boldsymbol{\delta}_{\mathrm{K}}$ can be determined by multiplying equation (3.11) with the inverse nodal Jacobian matrix as shown below:

$$\begin{bmatrix} \Delta\boldsymbol{\delta}_{\mathrm{K}} \\ \Delta\boldsymbol{u}_{\mathrm{K}} \end{bmatrix} = \boldsymbol{J}_{\mathrm{KK,L}}^{-1} \begin{bmatrix} \Delta\boldsymbol{p}_{\mathrm{K,G}} \\ \Delta\boldsymbol{q}_{\mathrm{K,G}} \end{bmatrix} \tag{3.12}$$

Due to the fact that the nodal Jacobian matrix $\boldsymbol{J}_{\mathrm{KK}}$ is singular, the main challenge of the determination of the sensitivity analysis is to invert this matrix. For this reason, the PFD uses the based on the generator currents Jacobian matrix $\boldsymbol{J}_{\mathrm{KK,L}}$, which is invertible.

The changes in the terminal active and reactive powers $\Delta\boldsymbol{p}_{\mathrm{T}}$ and $\Delta\boldsymbol{q}_{\mathrm{T}}$ depending on the terminal voltage $\Delta\boldsymbol{u}_{\mathrm{T}}$ and voltage angle $\Delta\boldsymbol{\delta}_{\mathrm{T}}$ changes can be calculated by:

$$\begin{bmatrix} \Delta\boldsymbol{p}_{\mathrm{T}} \\ \Delta\boldsymbol{q}_{\mathrm{T}} \end{bmatrix} = \begin{bmatrix} \dfrac{\partial\Delta\boldsymbol{p}_{\mathrm{T}}}{\partial\Delta\boldsymbol{\delta}_{\mathrm{T}}^{\mathrm{T}}} & \dfrac{\partial\Delta\boldsymbol{p}_{\mathrm{T}}}{\partial\Delta\boldsymbol{u}_{\mathrm{T}}^{\mathrm{T}}} \\ \dfrac{\partial\Delta\boldsymbol{q}_{\mathrm{T}}}{\partial\Delta\boldsymbol{\delta}_{\mathrm{T}}^{\mathrm{T}}} & \dfrac{\partial\Delta\boldsymbol{q}_{\mathrm{T}}}{\partial\Delta\boldsymbol{u}_{\mathrm{T}}^{\mathrm{T}}} \end{bmatrix} \begin{bmatrix} \Delta\boldsymbol{\delta}_{\mathrm{T}} \\ \Delta\boldsymbol{u}_{\mathrm{T}} \end{bmatrix} = \boldsymbol{J}_{\mathrm{T}} \begin{bmatrix} \Delta\boldsymbol{\delta}_{\mathrm{T}} \\ \Delta\boldsymbol{u}_{\mathrm{T}} \end{bmatrix} \tag{3.13}$$

where $\boldsymbol{J}_{\mathrm{T}}$ is the terminal Jacobian matrix.

On the other hand, the terminal currents $\underline{\boldsymbol{i}}_{\mathrm{T}}$ can be found using the transposed topological matrix $\boldsymbol{K}_{\mathrm{KT}}^{\mathrm{T}}$ as shown below:

$$\underline{\boldsymbol{i}}_{\mathrm{T}} = \underline{\boldsymbol{Y}}_{\mathrm{T}}\underline{\boldsymbol{u}}_{\mathrm{T}} = \underline{\boldsymbol{Y}}_{\mathrm{T}}\boldsymbol{K}_{\mathrm{KT}}^{\mathrm{T}}\underline{\boldsymbol{u}}_{\mathrm{K}} \tag{3.14}$$

Taking into account equation (3.13) the terminal voltage changes in equation (3.12) can be replaced by the node voltage $\Delta\boldsymbol{u}_{\mathrm{K}}$ and voltage angle $\Delta\boldsymbol{\delta}_{\mathrm{K}}$ changes using the transposed topological matrix. Finally, the node voltage changes can be expressed by the active $\Delta\boldsymbol{p}_{\mathrm{K,G}}$ and reactive $\Delta\boldsymbol{q}_{\mathrm{K,G}}$ power changes, which are based on the generator currents, as follows:

$$\begin{bmatrix} \Delta\boldsymbol{p}_{\mathrm{T}} \\ \Delta\boldsymbol{q}_{\mathrm{T}} \end{bmatrix} = \boldsymbol{J}_{\mathrm{T}}\boldsymbol{K}_{\mathrm{KT}}^{\mathrm{T}} \begin{bmatrix} \Delta\boldsymbol{\delta}_{\mathrm{K}} \\ \Delta\boldsymbol{u}_{\mathrm{K}} \end{bmatrix} = \boldsymbol{J}_{\mathrm{T}}\boldsymbol{K}_{\mathrm{KT}}^{\mathrm{T}}\boldsymbol{J}_{\mathrm{KK,L}}^{-1} \begin{bmatrix} \Delta\boldsymbol{p}_{\mathrm{K,G}} \\ \Delta\boldsymbol{q}_{\mathrm{K,G}} \end{bmatrix} \tag{3.15}$$

Nevertheless, there are some more methods for the *network sensitivity analysis*. An often-used method is the so-called *AC Power Transfer Distribution Factors* approach (AC-PTDF). It identifies the terminal apparent power changes, which result from the nodal active or reactive power change, as well as the PFD method. Therefore, the non-linear load flow equations can be linearized. [17]

The AC-PTDF calculation is based on equation (3.15) as well as the PFD. However, here all nodal currents, which consist of the load and generator currents, are considered. Therefore, the Jacobian matrix $\boldsymbol{J}_{\mathrm{KK}}$ in the AC-PTDF is calculated by the full nodal admittance matrix $\boldsymbol{Y}_{\mathrm{KK}}$. To invert the Jacobian matrix $\boldsymbol{J}_{\mathrm{KK}}$, an additional slack node, which automatically balances every imbalance of the active and reactive powers, is defined in the AC-PTDF. Hence, the equation number is reduced. Nevertheless, such balancing node does not exist in the real electric networks. [17]

The *sensitivity coefficient matrix* $\boldsymbol{\sigma}$ which describes the node impacts on power lines can be calculated as follows:

$$\boldsymbol{\sigma} = \boldsymbol{J}_{\mathrm{L}} \boldsymbol{J}_{\mathrm{KK,L}}^{-1} \tag{3.16}$$

with

$$\begin{bmatrix} \Delta \boldsymbol{p}_{\mathrm{L}} \\ \Delta \boldsymbol{q}_{\mathrm{L}} \end{bmatrix} = \boldsymbol{J}_{\mathrm{L}} \begin{bmatrix} \Delta \boldsymbol{\delta}_{\mathrm{K}} \\ \Delta \boldsymbol{u}_{\mathrm{K}} \end{bmatrix} = \begin{bmatrix} \dfrac{\partial \Delta \boldsymbol{p}_{\mathrm{L}}}{\partial \Delta \boldsymbol{\delta}_{\mathrm{K}}^{\mathrm{T}}} & \dfrac{\partial \Delta \boldsymbol{p}_{\mathrm{L}}}{\partial \Delta \boldsymbol{u}_{\mathrm{K}}^{\mathrm{T}}} \\ \dfrac{\partial \Delta \boldsymbol{q}_{\mathrm{L}}}{\partial \Delta \boldsymbol{\delta}_{\mathrm{K}}^{\mathrm{T}}} & \dfrac{\partial \Delta \boldsymbol{q}_{\mathrm{L}}}{\partial \Delta \boldsymbol{u}_{\mathrm{K}}^{\mathrm{T}}} \end{bmatrix} \begin{bmatrix} \Delta \boldsymbol{\delta}_{\mathrm{K}} \\ \Delta \boldsymbol{u}_{\mathrm{K}} \end{bmatrix} \tag{3.17}$$

where $\boldsymbol{J}_{\mathrm{L}}$ is the Jacobian matrix of power lines, $\Delta \boldsymbol{p}_{\mathrm{L}}$ and $\Delta \boldsymbol{q}_{\mathrm{L}}$ are the active and reactive power changes on power lines.

There are several often-used methods to define the slack node, which are described in [27]. To compare the PFD and AC-PTDF methods, two AC-PTDF approaches are utilized in this work [28], [29], [30].

The first approach allows to define one of the two in the redispatch participating generation nodes as a slack node (AC-PTDF method 1). If the input power of the second generator changes, the slack node balances the resulting active and reactive power mismatch. Hence, the interaction between both nodes can be interpreted as a redispatch action. To calculate the sensitivity coefficients, it is necessary to define every generation node as a slack bus iteratively. Therefore, the calculation time increases especially in the large electric networks. [17]

The second methodology is to define a random slack node (AC-PTDF method 2). In this approach, the calculated sensitivities are relative to this slack node. Therefore, it is important that the defined slack node has only a minor effect on the considered region. Furthermore, the total power generation and consumption must be balanced to reduce the influence of the slack node on the load flow situation. In this approach the calculation of sensitivity coefficients is based on a superposition, i.e. they are calculated by the effects from both generators related to the slack node. Due to the reduction of the randomly defined slack node, it is not possible to calculate the sensitivities of this node by this approach and the sensitivities on lines near the slack node are calculated too high. [17]

3.1.3 Comparison

The functionality and effectiveness of the introduced approaches for the sensitivity analysis are tested using standard electric network models in MATLAB ('5 Bus', '9 Bus' and '30 Bus' power flow test cases [31], [32]). For testing the method's accuracy, a redispatch of the active power for different power lines in the utilized power grid models is done to observe the dependency of the current change on the active power change on these lines, as well as different line congestions are created.

3.1.3.1 '5 Bus' IEEE power grid model

The '5 Bus' IEEE power grid model, which is used in this work to compare the methods for the sensitivity analysis, includes [31] and is shown in Figure 3.2:

- 5 bus bars ('N4' is a slack node)
- 3 power plants
- 6 lines
- 3 loads

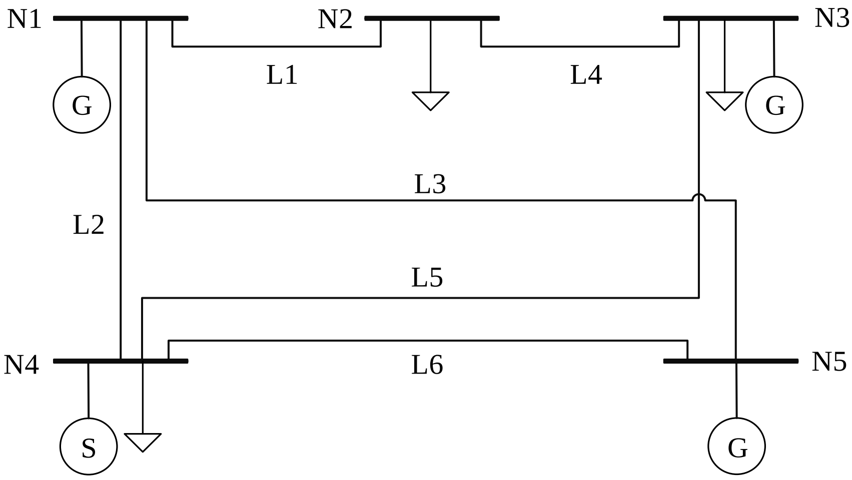

Figure 3.2 ‘5 Bus’ IEEE power grid model

All six power lines in the ‘5 Bus’ IEEE power grid model are studied. To observe the dependency of the current change on the active power change on line ‘L1’, the power plants connected to bus bars ‘N1’ and ‘N3’ are selected for the redispatching because they have the biggest influence on the considered line based on the sensitivity analysis.

Figure 3.3 represents the dependency of the current change on the active power change on the considered line. The blue curve shows the I-P characteristic for the non-linear load flow function, the red one – a load flow approximation using the PFD method, the orange one – an approximation using the AC-PTDF method 1 and the purple one – an approximation with the AC-PTDF method 2.

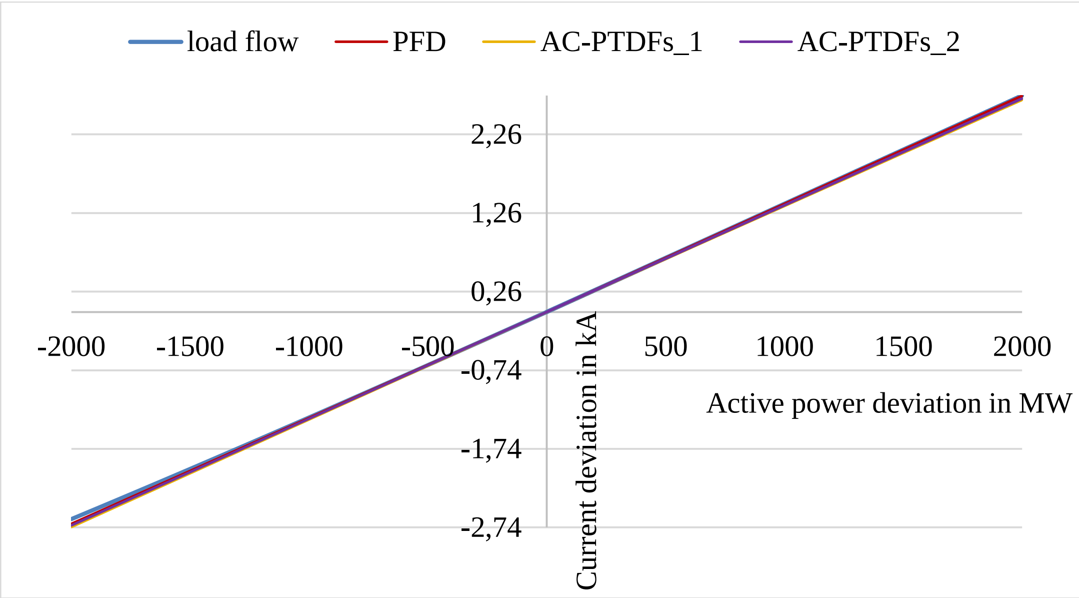

Figure 3.3 I-P characteristics for the line ‘L1’ in the ‘5 Bus’ IEEE test network model

Based on the I-P characteristics for the line ‘L1’, all sensitivity analysis methods have small deviations from the power flow function so that all curves are close to each other. Therefore, their zoomed representation to show which method is more accurate is given in Figure 3.4.

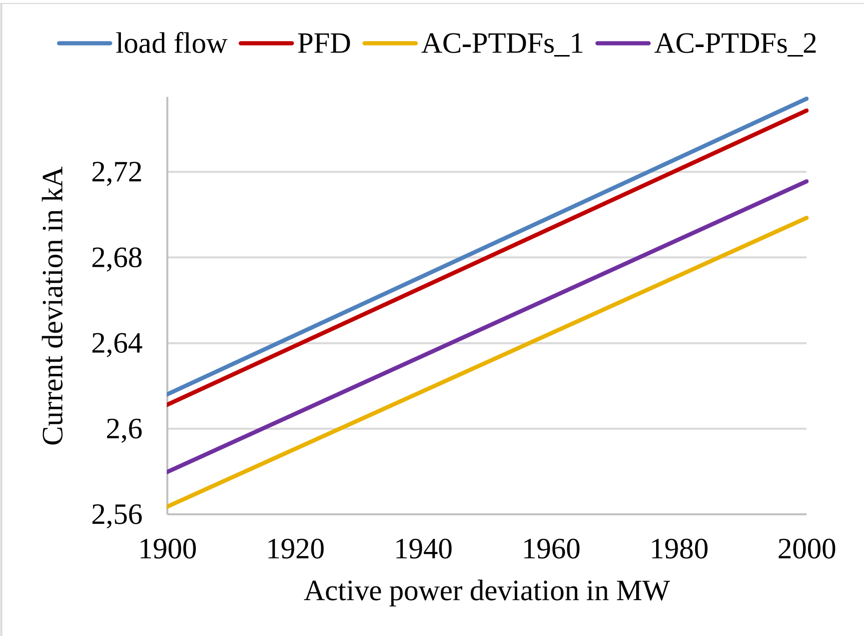

Figure 3.4 I-P characteristics for the line ‘L1’ in the ‘5 Bus’ IEEE test network model (zoomed representation)

Obviously, the PFD approximates the non-linear load flow function most accurately in this test case. However, the AC-PTDF methods 1 and 2 provide accurate results as well.

Furthermore, to observe the dependency of the current change on the active power change on line ‘L3’, the power plants with the biggest influence on the considered line, which are connected to bus bars ‘N1’ and ‘N5’, are selected for the redispatch realization. Figure 3.5 represents the dependency of the current change on the active power change on line ‘L3’.

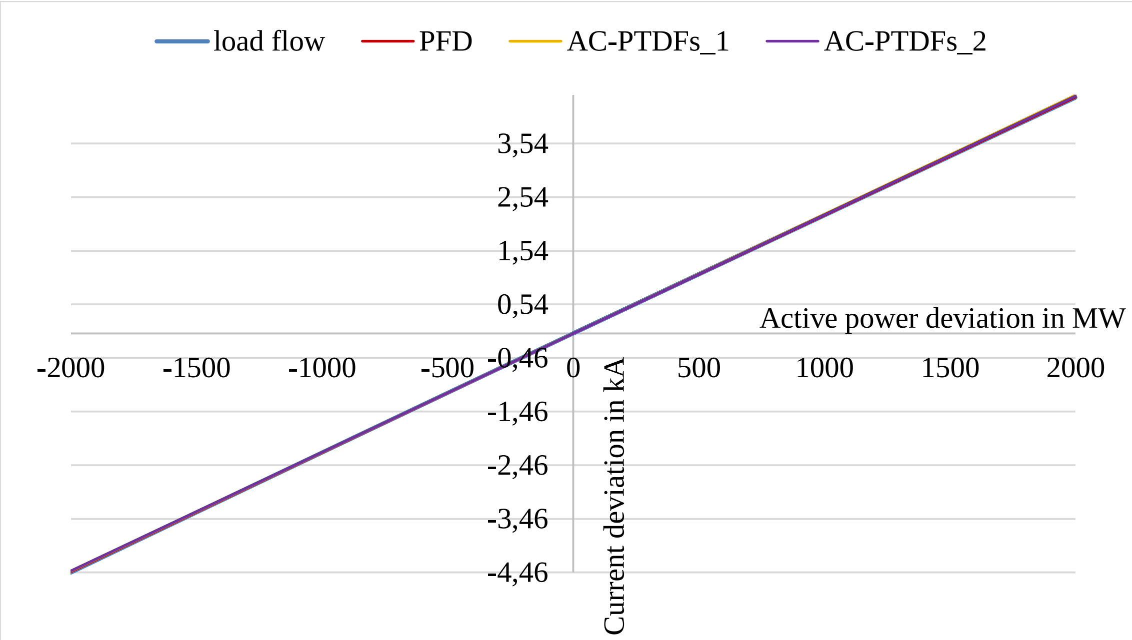

Figure 3.5 I-P characteristics for the line ‘L3’ in the ‘5 Bus’ IEEE test network model

Here, the approaches provide small deviations as well as by the approximations in the previous case. For this reason, a zoomed representation of the I-P characteristics for the line ‘L3’ is given on Figure 3.6.

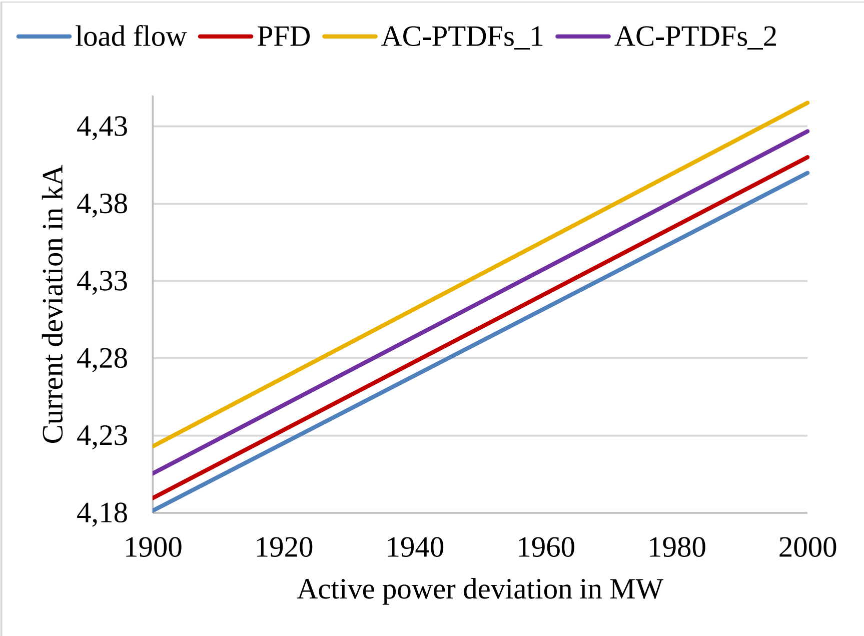

Figure 3.6 I-P characteristics for the line ‘L3’ in the ‘5 Bus’ IEEE test network model (zoomed representation)

In this case, the PFD method provides the most accurate results again. But the AC-PTDF approaches have only small deviations too.

3.1.3.2 Simplified grid model of the ENTSO-E area

The simplified grid model of the ENTSO-E area, which is described in detail in chapter 5.1.2 and shown in Figure 5.3, is also utilized to compare the introduced methods for the sensitivity analysis.

To observe the dependency of the current change on the active power change on the double power line between bus bars ‘1’ and ‘2’, the power plants with the biggest influence on the considered line, which are connected to bus bars ‘1’ and ‘2’, are selected for the redispatching. Figure 3.7 represents the dependency of the current change on the active power change on this power line.

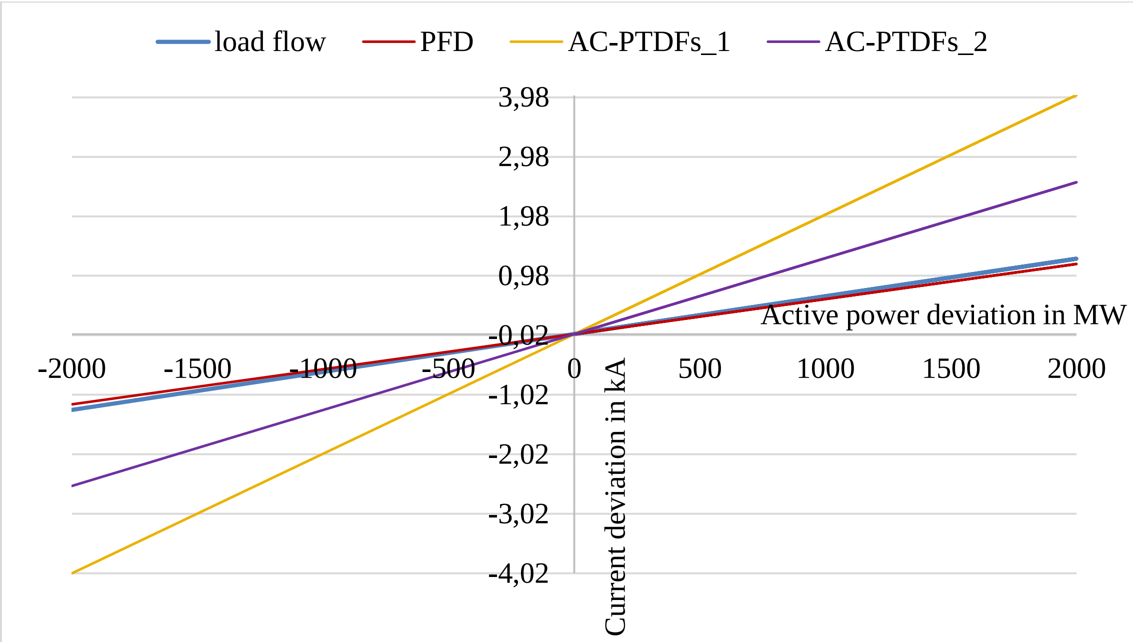

Figure 3.7 I-P characteristics for the line power line between bus bars ‘1’ and ‘2’

Here, the PFD provides a very accurate approximation, while the AC-PTDF methods 1 and 2 approximate the non-linear load flow function with large deviations.

In addition, to observe the dependency of the current change on the active power change on the double power line between bus bars ‘11’ and ‘19’, the power plants with the biggest influence on the considered line, which are connected to bus bars ‘11’ and ‘19’, are selected for the redispatch realization. Figure 3.8 represents the dependency of the current change on the active power change on this power line.

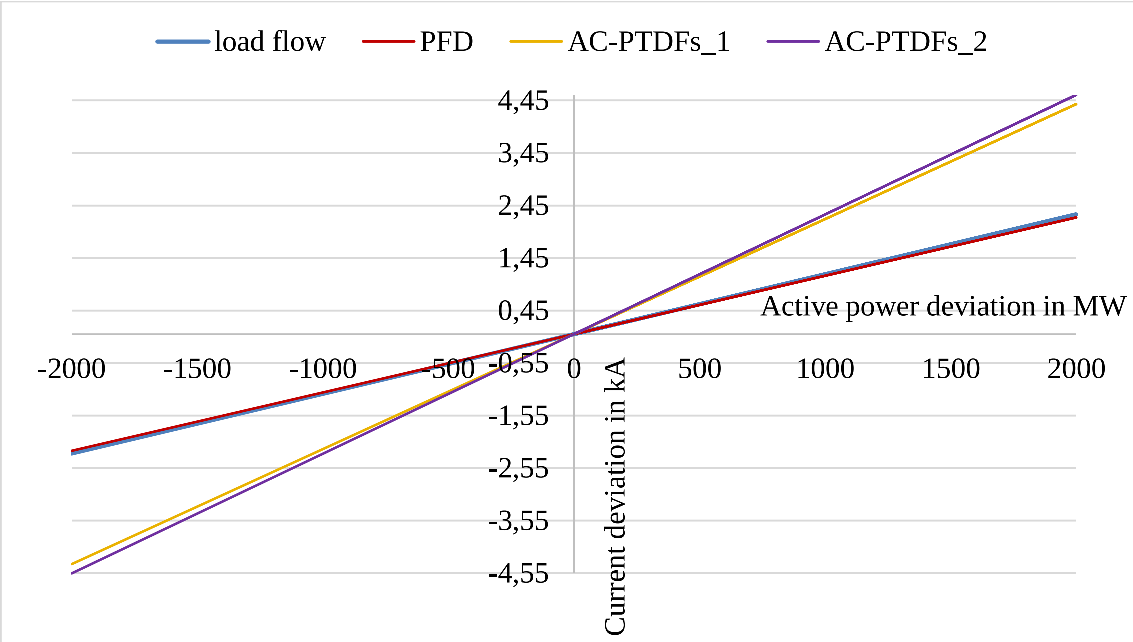

Figure 3.8 I-P characteristics for the line power line between bus bars ‘11’ and ‘19’

Obviously, the sensitivity analysis methods provide similar results as well as in the previous case.

3.1.3.3 Conclusions

Based on the simulation results for the standard IEEE test power grid models and simplified ENTSO-E grid model, the PFD approach provides the most accurate approximations of the non-linear load flow function in all test models. Its maximum deviation is around 9% in case of a high load in the simplified grid model of the ENTSO-E area. However, the AC-PTDF methods 1 and 2 can have extremely large approximation deviations up to 100% and more in the utilized power grid models. Therefore, in this work, the calculation of the network sensitivity analysis is done by the PFD method.

3.2 Economic aspects of redispatch

Since redispatching is a very often used remedial action by the TSOs and can cause enormous costs, it should be realized cost-efficiently to avoid high expenses. In this respect, some economic aspects, e.g. electricity generation costs, start-up and shut-down costs of the power plants, which participate in the redispatch, should be considered. [4]

3.2.1 Levelized costs of electricity

For the redispatch realization it is important to consider the so-called *levelized costs of electricity* (LCOE) c_{LCOE}. These costs need to be spent on an energy conversion from any form of energy to electricity [33]. They are usually given in euros per kWh and consist of:

- initial investment
- costs of capital
- operating cost
- costs of fuel
- maintenance cost

The total LCOE for different conventional power plant types are provided in Table 3.1 [34], [35].

Table 3.1 LCOE for different conventional power plant types [34]

Power plant LCOE in €/MWh \Power plant types	***average***	***min***	***max***
Lignite-fired power plants	63	46	80
Hard coal-fired power plants	81	63	99
Combined cycle gas turbine power plants	89	78	100
Gas turbine power plants	165	110	219

3.2.2 Power plant cycling costs

Furthermore, the *power plant cycling costs* (PPCC) can be also taken into account by the redispatch realization. Cycling of a power plant is its operation depending on different load levels. Here, the power plants are permanently switched on and off, which can cause an equipment damage because of large pressure and thermal stresses during these processes. The PPCC can be classified in general in five groups [36], [37]:

- fuel, auxiliary services and CO_2 emission costs related to the start-up, also called *direct start-up costs*
- equipment replacement and maintenance costs related to the start-up, also called *indirect start-up costs*
- equipment replacement and maintenance costs related to the load following, also called *ramping costs*
- *forced outage costs* related to the start-up i.e. opportunity costs for the power generation during a power plant outage
- heat rate effects related to the power plant cycling

Therefore, the total PPCC $c_{\mathrm{su},i}$ can be calculated as shown below:

$$c_{\mathrm{su},i} = c_{\mathrm{su\_dir},i} + c_{\mathrm{su\_indir},i} + c_{\mathrm{ramp},i} + c_{\mathrm{fo},i} + c_{\mathrm{hr\_incr},i} \tag{3.18}$$

where $c_{\mathrm{su\_dir},i}$ is the direct start-up costs, $c_{\mathrm{su\_indir},i}$ is the indirect start-up costs, $c_{\mathrm{ramp},i}$ is the ramping costs, $c_{\mathrm{fo},i}$ is the forced outage costs, $c_{\mathrm{hr\_incr},i}$ is the costs due to the heat rate increase.

Furthermore, the indirect start-up costs are depending on the time, during which the power plant was offline: the longer it was offline, the higher the indirect start-up costs. There are three types of the power plant start-up regarding the offline time [38]:

- *hot start* if the power plant was offline less than 24 hours before the start-up process
- *warm start* if the power plant was offline between 25-119 hours before the start-up process
- *cold start* if the power plant was offline for 120 hours or more before the start-up process

The indirect start-up costs are an exponential function based on the start-up loss dependency from the offline time t of the power plant time [39], [40] and can be determined as follows [41], [42]:

$$c_{\mathrm{su\_indir},i} = c_{\mathrm{su\_indir,max},i}(1 - \mathrm{e}^{-\lambda_i \cdot t}) \tag{3.19}$$

where $c_{\mathrm{su\_indir,max},i}$ is the maximum of the indirect start-up costs for the power plant i and λ_i is the heat-loss coefficient which is defined between 0 and 1.

Figure 3.9 shows the dependency of the indirect start-up costs from the time during which the power plant was offline (the green curve). The orange lines are average values of the indirect start-up costs for three types of the power plant start-up.

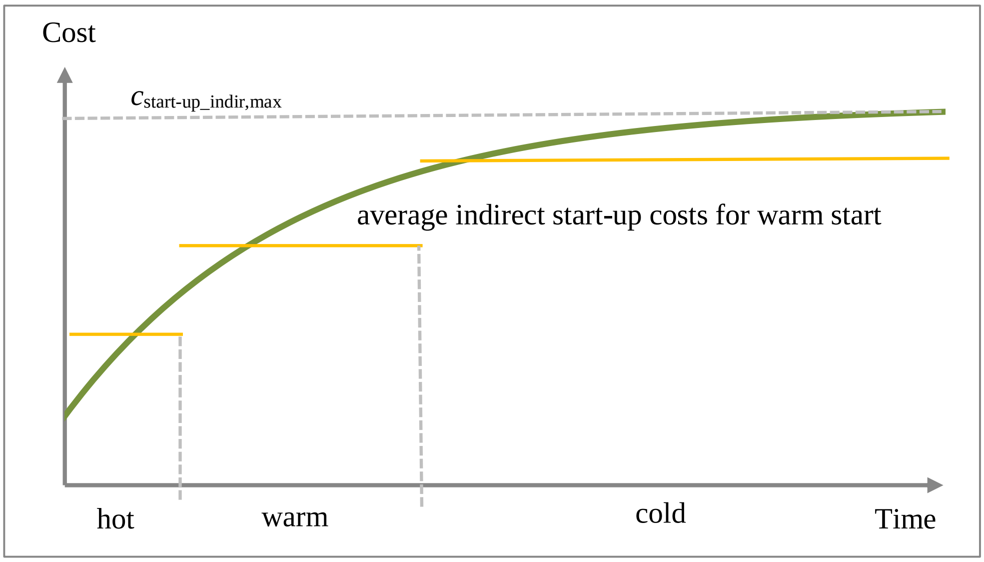

Figure 3.9 Indirect start-up cost function [41]

The total PPCC for different conventional power plant types are provided in Table 3.2. These costs were originally calculated in US dollars for the United States in 2011 [36]. However, for this work, they are converted into euros regarding the average dollar exchange rate in 2011.

Table 3.2 Cycling costs for different conventional power plant types [36]

Power plant cycling cost types	**Direct**			**Indirect**			**Ramping**		
Costs in €/MW \Power plant types	***hot start***	***warm start***	***cold start***	***ave-rage***	***min***	***max***	***ave-rage***	***min***	***max***
Coal-fired power plant (small subcritical)	7	9	12	96	67	143	10	7	11
Coal-fired power plant (large subcritical)	9	13	17	55	38	65	11	6	13
Coal-fired power plant (super critical)	11	19	23	53	40	65	8	5	10

Power plant cycling cost types	Direct			Indirect			Ramping		
Gas-based combined cycle power plant	-	-	-	41	25	60	1.5	0.7	1.6
Gas-fired power plant	1	1	1	63	19	74	3.5	2	6
Power plant with aero-derivative gas turbine	3	3	3	18	9	44	0.5	0.4	1.2
Gas-fired steam power plant	6	10	15	41	28	52	6	3.4	7

Power plant cycling cost types	Forced outage		
Costs in €/MW \Power plant types	***hot start***	***warm start***	***cold start***
Coal-fired power plant (small subcritical)	1	2	3.4
Coal-fired power plant (large subcritical)	0.4	0.5	1.4
Coal-fired power plant (super critical)	0.3	0.6	0.9
Gas-based combined cycle power plant	0.3	0.6	0.6
Gas-fired power plant	0.5	1.7	1
Power plant with aero-derivative gas turbine	0.8	0.8	0.9
Gas-fired steam power plant	0.2	0.5	0.8

Due to the heat rate increase, the costs can be are neglected because they are very small compared to other cost types [36].

The indirect PPCC for different conventional power plant types are provided in detail in Table 3.3. These costs are converted into euros as well.

Table 3.3 Indirect cycling costs for different conventional power plant types [36]

Power plant start-up types	Hot start			Warm start			Cold start		
Indirect cycling costs in €/MW \Power plant types	***ave-rage***	***min***	***max***	***ave-rage***	***min***	***max***	***ave-rage***	***min***	***max***
Coal-fired power plant (small subcritical)	68	57	94	113	80	130	106	63	205
Coal-fired power plant (large subcritical)	42	28	49	47	40	56	75	45	89
Coal-fired power plant (super critical)	39	28	45	46	39	64	75	52	86
Gas-based combined cycle power plant	25	20	40	40	23	67	57	33	73
Gas-fired power plant	23	16	34	91	19	104	74	22	85

Power plant start-up types	Hot start			Warm start			Cold start		
Power plant with aero-derivative gas turbine	14	9	44	17	9	44	23	9	44
Gas-fired steam power plant	26	18	30	42	26	63	54	39	64

Due to difficulty of the PPCC calculation, the total PPCC are rarely involved in making decisions of the unit commitment by the system operators. Therefore, only the direct start-up costs are usually considered even though they can be a small part of the total PPCC. [37]

3.2.3 Shut-down costs

In addition, the *power plant shut-down costs* (PPSDC) c_{sd} for different conventional power plant types can be considered by the redispatch realization as well. However, in contrast to the power plant cycling costs, they are considerably lower. [43], [44], [45]

The total PPSDC for different power plant types are provided in Table 3.4 [45].

Table 3.4 PPSDC for different conventional power plant types [45]

Power plant shut-down costs in €/MW \Power plant types	*average*
Coal-fired steam power plants	1.6
Combined-cycle gas turbines	2.2

4 Optimization methods

First of all, to solve an optimization problem, a suitable optimization method must be chosen. The selected technique should provide sufficiently accurate solutions in a short time. The choice of the optimization algorithm strongly depends on the formulation of the optimization problem, resp. of its objective function and constraints.

There is a wide range of optimization methods for solving different optimization problems. Therefore, the big challenge in this field is to extract a suitable optimization technique from the many existing methods. Furthermore, some optimization algorithms are specifically developed for a certain kind of optimization task, e.g. the linear programming for problems with a linear criteria and linear constraints. In addition, various optimization methods can usually be used to solve one specific problem.

The optimization techniques, which are suitable for the redispatch optimization, are introduced in this chapter.

4.1 Linear programming

The *Linear Programming* (LP) is a very common optimization technique to solve optimization problems, which include only a linear objective function (4.1) and linear constraints (4.2). It is used in different areas, e.g. industry, medicine, economy, engineering, computer science etc. The main objective of the LP is to maximize or minimize the linear function over a polyhedron. [46], [47], [48], [49], [50]

$$f\left(x_1, x_2 ..., x_n\right) = c_1 x_1 + c_2 x_2 + ... + c_n x_n$$
$$\text{or} \tag{4.1}$$
$$f\left(x_j\right) = \sum_{j=1}^{n} c_j x_j, \quad (j = 1, 2 ..., n)$$

subject to:

$$\begin{aligned} a_{11}x_1 + a_{12}x_2 + \ldots + a_{1n}x_n &\le b_1 \\ a_{21}x_1 + a_{22}x_2 + \ldots + a_{2n}x_n &\le b_2 \\ &\ldots \\ a_{m1}x_1 + a_{m2}x_2 + \ldots + a_{mn}x_n &\le b_m \\ &\text{or} \\ \sum_{j=1}^{n} a_{ij}x_i \le b_i, \quad (i &= 1, 2\ldots, m) \end{aligned} \tag{4.2}$$

where $f(x_j)$ is the linear function, x_j – the searched variables, a_{ij}, b_i, c_j – the real numbers, n – the number of function variables, m – the number of constraints.

Based on equations (4.1) and (4.2), the LP problem with the objective function $\boldsymbol{c}$ can be formulated in the following standard matrix form [46], [47], [48], [49], [50]:

$$\min_{x}\left(\boldsymbol{c}^{\mathrm{T}}\boldsymbol{x}\right) \tag{4.3}$$

subject to:

$$\boldsymbol{Ax} \le \boldsymbol{b} \tag{4.4}$$

where the linear constraints are expressed by the vector of the searched variables $\boldsymbol{x}$, matrix of the constraint system $\boldsymbol{A}$ and vector of the constraint restrictions $\boldsymbol{b}$.

4.1.1 Simplex algorithm

The *simplex method* or *simplex algorithm* is a frequently used algorithm for solving optimization problems of the LP developed by George Danzig in 1947 [46], [47]. This method finds an exact solution of an optimization problem after a finite number of iteration steps or determines its infeasibility.

4.1.1.1 General approach

The *simplex algorithm* solves optimization problems with the objective function $\boldsymbol{c}$ and constraints in the form described by equations (4.3) and (4.4). It consists of two main steps. [46], [47]:

1. determination of a starting solution, which must fulfil the constraints (usually not the optimal solution) or infeasibility of the optimization problem.
2. iterative improvement of the current solution of the optimization problem until an optimal solution is found, i.e. an improvement of the objective function is not possible anymore.

At each iteration step the so-called simplex tableau $\boldsymbol{T}$ is calculated anew to find the most suitable edge of the polyhedron, resp. the optimal solution [4], [15]:

$$\boldsymbol{T} = \begin{bmatrix} \boldsymbol{A} & \boldsymbol{I} & \boldsymbol{b} \\ \boldsymbol{c}^{\mathrm{T}} & 0 & f \end{bmatrix} \tag{4.5}$$

with the identity matrix $\boldsymbol{I}$ and value of the cost function f, which is determined as shown in equation (4.3).

For every iteration the *pivot element* in the simplex tableau must be found. Here, the pivot column is the column with the smallest negative coefficient of $\boldsymbol{c}^{\mathrm{T}}$ and the pivot row is the row with the smallest nonnegative quotient of $\boldsymbol{b}$ and the pivot column of $\boldsymbol{A}$. Then the pivot column is transformed to a unit vector regarding the pivot element. These calculation steps are equivalent to the Gaussian elimination, resp. to the steps by solving a linear system of equations. They lead to a new optimization problem solution, resp. to a new edge of the polyhedron with more optimal objective function value.

4.1.1.2 Performance

Nowadays, the *simplex algorithm* is widely and constantly utilized in various fields around the world to solve linear programming problems. This is the greatest proof of its high performance. There are several main advantages, which make the simplex extremely popular [46], [47]:

- It is based on a simple calculation method and is easily understandable.
- It is easy to implement.
- It has a low computation time, especially by small linear programming problems.
- It considers different factors and restrictions of the optimization problem by every iteration step instead of guessing the optimal solution.

Nevertheless, there are some disadvantages of the simplex algorithm, which should be considered by choosing an optimization method:

- It can only be utilized for certain linear programming tasks, which requires an adaptation of the optimization problem.
- It is not the fastest analytical optimization method.
- During solving the optimization problem an infinite loop can occur by a careless choice of the pivot elements.

4.1.2 Linear redispatch optimization

4.1.2.1 Objective function of the redispatch optimization problem

Here, the costs c for the realization of the redispatch, which should be minimized as shown in equation (4.3), is used as the *objective function* for the considered optimization problem and is formulated as follows [4], [15], [17], [46], [47]:

$$c = \sum_{i=1}^{G} \sum_{j=1}^{G} \Delta P_{ij} \Delta c_{ij} \tag{4.6}$$

with

$$\Delta P_{ij} = P_{\mathrm{incr},i} = -P_{\mathrm{red},j} \tag{4.7}$$

$$\Delta c_{ij} = c_{\mathrm{incr},i} - c_{\mathrm{red},j} \tag{4.8}$$

where ΔP_{ij} is the amount of the power generation change for every possible power plant pair during the redispatching, $P_{\text{incr},i}$, $P_{\text{red},j}$ are the amount of the power generation increase/reduction for each power plant, Δc_{ij} is the costs in €/MWh, which must be spent for the power generation change by every possible power plant pair, $c_{\text{incr},i}$, $c_{\text{red}j}$ are the cost, which must be spent/saved for the increasing/reducing of the power generation for each power plant and G is the number of the power plants in the power grid.

4.1.2.2 Constraints of the redispatch optimization problem

The main constraint for the introduced redispatch optimization problem is considering the electric network state, i.e. power flow, and node impact on the congested line. The easiest and most efficient way to formulate this constraint is a linearization of the non-linear power flow equations using the network sensitivity analysis:

$$\sum_{i=1}^{G}\sum_{j=1}^{G}\Delta P_{ij}\Delta\sigma_{ij} \geq P_{\text{cong}} \tag{4.9}$$

with

$$\Delta\sigma_{ij} = \sigma_{\text{incr},i} - \sigma_{\text{red},j} \tag{4.10}$$

where $\Delta\sigma_{ij}$ is the difference between the sensitivity coefficients for every possible power plant pair during the redispatching, $\Delta\sigma_{\text{incr},i}$, $\Delta\sigma_{\text{red},j}$ are the sensitivity coefficients for each power plant.

In this work, the PFD, which is introduced in chapter 3.1.2, is used to calculate the network sensitivities, resp. to formulate the first constraint in equation (4.9) of the considered redispatch optimization problem.

The further important constraints for the optimization problem are the consideration of the power plant redispatch potentials, which can be utilized during the redispatch realization. These constraints consider the maximum and minimum active powers, which can be generated by the power plants.

$$\sum_{j=1}^{G} \Delta P_{ij} - \sum_{j=1}^{G} \Delta P_{ji} \leq P_{\mathrm{RP+},i} \tag{4.11}$$

$$\sum_{j=1}^{G} \Delta P_{ji} - \sum_{j=1}^{G} \Delta P_{ij} \leq P_{\mathrm{RP-},i} \tag{4.12}$$

where $P_{\mathrm{RP+},i}$ and $P_{\mathrm{RP-},i}$ are the positive and negative redispatch potentials of the power plant i.

4.1.3 Sequential simplex

4.1.3.1 General approach

The *sequential simplex* (SS) is an extension of the standard *simplex algorithm* and was proposed by W. Spendley, G.R. Hext and F.R. Himsworth in 1962. This technique utilizes the simplex sequentially, i.e. each subsequent simplex run starts with the last working point of the previous run, resp. they both always have one common edge. Therefore, calculation errors can be completely remedied in this way. [51], [52]

The SS was further developed by J. A. Nelder and R. Meadf in 1965. In this approach, the *objective function* with n variables is minimized compressing the function values at n+1 vertices, resp. positions p of the standard simplex. Thereby, the highest vertex p_h with the maximum value must be replaced by another working point. Therefore, the SS adjusts itself to the local minimum to finally find the global minimum.

Firstly, the initial vertex p_1 is randomly chosen. Then the remaining vertices p_i need to be scaled by [52] [53]:

$$p_i = p_1 + \lambda_i \boldsymbol{u}^{(i-1)} \tag{4.13}$$

where i=2,…,n+1, λ_i – the positive constants and $\boldsymbol{u}$ – the unit vector.

Furthermore, the so-called *centroid* of the simplex p_c should be calculated without consideration of the highest vertex as follows [52]:

$$p_{\mathrm{c}} = \sum_{i=2}^{n+1} p_i \tag{4.14}$$

The *reflection* p_{r}, which is the main operation of the SS, is determined by:

$$p_{\mathrm{r}} = p_{\mathrm{c}} + \alpha_1 (p_{\mathrm{c}} - p_{\mathrm{h}}) \tag{4.15}$$

where α_1 is the reflection coefficient, which is greater than 0 and is calculated as following [52]:

$$\alpha_1 = \left| \frac{p_{\mathrm{r}} - p_{\mathrm{c}}}{p_{\mathrm{h}} - p_{\mathrm{c}}} \right| \tag{4.16}$$

If the function value f_{r} of the reflection p_{r} is smaller than the function value f_{l} of the lowest vertex p_{l}, the so-called *expansion* must be done:

$$p_{\mathrm{e}} = p_{\mathrm{c}} + \alpha_2 (p_{\mathrm{r}} - p_{\mathrm{c}}) \tag{4.17}$$

with

$$\alpha_2 = \left| \frac{p_{\mathrm{e}} - p_{\mathrm{c}}}{p_{\mathrm{r}} - p_{\mathrm{c}}} \right| \tag{4.18}$$

If the function value f_{e} of the expansion p_{e} is smaller than the function value f_{l} of the lowest vertex p_{l}, the highest vertex p_{h} is replaced by the expansion. Here, the reflection p_{r} must be recalculated taking into account the new expansion value.

If the function value f_{e} is greater than the function value f_{l}, the highest vertex p_{h} is replaced by the reflection. Then the reflection p_{r} must be recalculated as well.

However, if the function value f_{r} of the reflection p_{r} is greater than the function value f_{l} of the lowest vertex p_{l}, the highest vertex p_{h} is immediately replaced by the reflection p_{r}.

After that the so-called *contraction* p_{contr} is calculated as follows:

$$p_{contr} = p_{\mathrm{c}} + \alpha_3 (p_{\mathrm{h}} - p_{\mathrm{c}}) \tag{4.19}$$

where α_3 is the contraction coefficient, which is determined by:

$$\alpha_3 = \left| \frac{p_{\text{contr}} - p_{\text{c}}}{p_{\text{h}} - p_{\text{c}}} \right| \tag{4.20}$$

with

$$0 \leq \alpha_3 \leq 1 \tag{4.21}$$

If the function value f_{contr} of the contraction is smaller than the minimum value of the function values f_{h} and f_{r}, the highest vertex p_{h} is replaced by the contraction p_{contr}. Here, the reflection p_{r} must be recalculated again.

Finally, if the f_{contr} is greater than the minimum value of the f_{h} and f_{r}, all positions p_i should be replaced using:

$$p_i = \frac{p_i + p_{\text{l}}}{2} \tag{4.22}$$

Then the reflection must be recalculated.

If the global minimum is reached, the iterative process is stopped.

4.1.3.2 Algorithm adaptation for the non-linear redispatch optimization problem

To avoid deviations in the congestion power calculation, which are caused by the utilization of the sensitivity analysis, the SS is used in this work as well.

The optimization begins from a run of the standard simplex taking into account the linear redispatch optimization, which is described in detail in chapter 4.1.2. Here, the found power changes of power plants for the redispatch realization are used to create a new working point of the power grid. Then the power flow of this new working point is determined using the non-linear load flow equations.

If there is deviation in the congestion power calculation, this deviation is utilized as the congestion power on the congested line in equation (4.9) for the next run of the simplex. Furthermore, before the next run, the network sensitivity analysis for the new working point are calculated again. Therefore, the new sensitivity coefficients are taken for the redispatch optimization using equation (4.9). In addition, the power plant redispatch potentials are recalculated as well. This procedure repeats until the network congestion is completely remedied.

4.2 Genetic algorithm

The *genetic algorithm* (GA) is a stochastic evolutionary optimization method, which is based on principles of Darwin's theory of biological evolution such as genetic inheritance and natural selection. It was developed by Prof. John Holland and his students at the University of Michigan in the early 1970s. The GA is very well suited for solving highly nonlinear optimization problems and is able to find the global optimal solution in a complex search space. It is utilized in a variety of areas, e.g. engineering, robot technology, bioinformatics, computer science, economy, chemistry, transport etc. [54], [55], [56], [57], [58], [59], [60], [61]

4.2.1 Evolutionary optimization algorithms

The *Evolutionary algorithms* (EA) are a subset of stochastic optimization methods, which are based on evolutionary mechanisms such as a selection, mutation, recombination and reproduction. The EAs cannot usually find the best solution but a well approximating one for every optimization problem type. Furthermore, they are easily implementable. This all makes them applicable in a broad range of fields. [55], [56]

The recombination and mutation operators of the EAs can extend the search space. But it does not provide any guarantee that the current problem solution will be improved. However, the search procedure always moves to a global optimum by means of the selection. [57]

There are plenty of evolutionary algorithm types and variations. The evolutionary algorithms differ mainly in the genetic representation, genetic operators and objective function of the optimization problem.

In this work, the *genetic algorithm* and its variation are introduced and evaluated. The basic principles of these optimization methods are described in this chapter

4.2.2 General approach

In contrast to the *simplex algorithm*, the GA can solve optimization problems with the fitness function $\boldsymbol{c}$ and constraints which can be formulated by linear, non-linear, discrete or discontinues equations [4], [15], [54], [57]:

$$\max_{x}\left(f\left(\boldsymbol{x}\right)\right) \tag{4.23}$$

Assumed:

$$\boldsymbol{A}\left(\boldsymbol{x}\right) \leq \boldsymbol{b} \tag{4.24}$$

As well as all *evolutionary algorithms*, the GA is an iterative process, which begins with the generation of an initial population. This start population consists of chromosomes which are randomly created. Furthermore, before the population initialization, the objective function, constraints of the optimization problem and GA parameters must be defined. Then the recombination of the best chromosomes is realized, resp. the strongest individuals produce an offspring. In the next step, a new generation is created based on the best individuals and their offspring. After that the new generation mutates and the strongest individuals of this generation are chosen for the next iteration step. The above process repeats until break conditions, e.g. finding an acceptable solution or exhaustion of the iteration steps, are fulfilled. A flowchart of the described iterative process is given in Figure 4.1 [4], [54], [55], [59]

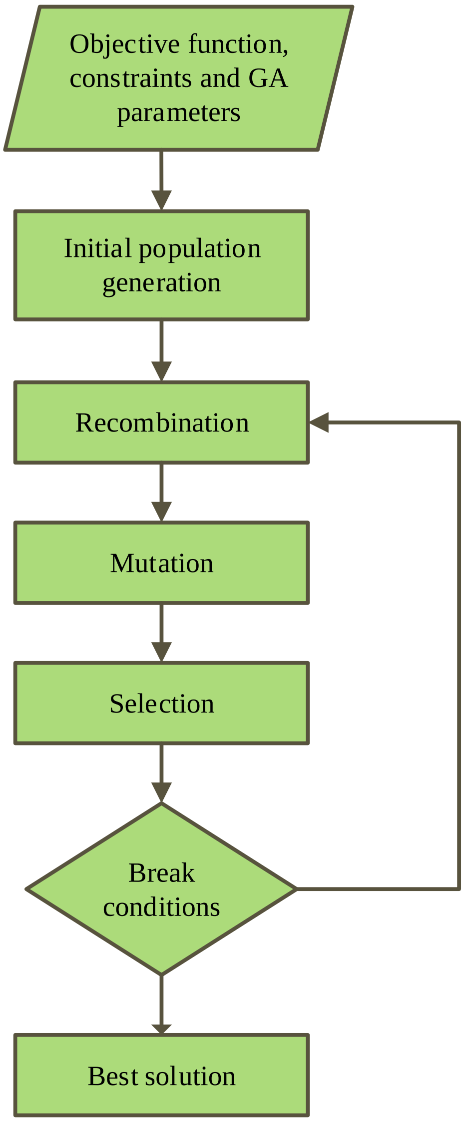

Figure 4.1 Flowchart of the genetic algorithm

4.2.2.1 Recombination

There are various methods for mating the best individuals/chromosomes in the GAs. But the simplest and in many cases well working mating approach is choosing one crossover point in the two parent chromosomes $\boldsymbol{c}_{\mathrm{m}}$ and $\boldsymbol{c}_{\mathrm{f}}$ [54].

$$\begin{aligned}\boldsymbol{c}_{\mathrm{m}} &= [c_{\mathrm{m}1}, c_{\mathrm{m}2}, ..., c_{\mathrm{m}crp}, ..., c_{\mathrm{m}n}] \\ \boldsymbol{c}_{\mathrm{f}} &= [c_{\mathrm{f}1}, c_{\mathrm{f}2}, ..., c_{\mathrm{f}crp}, ..., c_{\mathrm{f}n}]\end{aligned} \tag{4.25}$$

where $c_{\mathrm{m}1}$, $c_{\mathrm{m}2}, \ldots c_{\mathrm{m}n}$ are the variables of the 'mother' chromosome, $c_{\mathrm{f}1}$, $c_{\mathrm{f}2}, \ldots c_{\mathrm{f}n}$ – the variables of the 'father' chromosome, n – the number of the chromosome variables and $c_{\mathrm{m}crp}$, $c_{\mathrm{f}crp}$ – the crossover point, i.e. the chromosome variables are randomly exchanged in the crossover point. Therefore, two new offspring chromosomes $\boldsymbol{c}_{\mathrm{offspr1}}$ and $\boldsymbol{c}_{\mathrm{foffspr2}}$ are produced:

$$\begin{aligned}\boldsymbol{c}_{\mathrm{offspr1}} &= [c_{\mathrm{m}1}, c_{\mathrm{m}2}, ..., c_{\mathrm{f}crp}, ..., c_{\mathrm{f}n}] \\ \boldsymbol{c}_{\mathrm{offspr2}} &= [c_{\mathrm{f}1}, c_{\mathrm{f}2}, ..., c_{\mathrm{m}crp}, ..., c_{\mathrm{m}n}]\end{aligned} \tag{4.26}$$

However, the big disadvantage of this approach that there is no new genetic material in the offspring at all: the offspring is only a new combination of the parents. Consequently, a new genetic material can only appear by a mutation.

To solve this problem an extrapolation can be used in the introduced crossover method, i.e. new variable values c_{new1} and c_{new2}, which are based on different combinations of the parent variable values, are integrated in the offspring [54].

$$\begin{aligned}c_{\mathrm{new1}} &= c_{\mathrm{m}crp} - \beta\left(c_{\mathrm{m}crp} - c_{\mathrm{f}crp}\right) \\ c_{\mathrm{new2}} &= c_{\mathrm{f}crp} + \beta\left(c_{\mathrm{m}crp} - c_{\mathrm{f}crp}\right)\end{aligned} \tag{4.27}$$

where β is the random number between 0 and 1.

Then these calculated values are integrated into equation (4.25) instead of the crossover point as given by

$$\begin{aligned}\boldsymbol{c}_{\mathrm{offspr1}} &= [c_{\mathrm{m}1}, c_{\mathrm{m}2}, ..., c_{\mathrm{new1}}, ..., c_{\mathrm{f}n}] \\ \boldsymbol{c}_{\mathrm{offspr2}} &= [c_{\mathrm{f}1}, c_{\mathrm{f}2}, ..., c_{\mathrm{new2}}, ..., c_{\mathrm{m}n}]\end{aligned} \tag{4.28}$$

If the crossover point is the first chromosome variables, the remaining variables of the parent chromosomes to the right are exchanged. If the crossover point is the last chromosome variables, the remaining variables of the parent chromosomes to the left are exchanged. [54]

After the recombination a new generation, which can consist of the parent and offspring chromosomes are created.

4.2.2.2 Mutation

With the help of the recombination the GA can find a global minimum very fast. However, such approximate solutions are not enough to fulfill the task in many cases: a local minimum must be found as well. For this reason, a mutation operator is utilized in the GAs. It introduces a new genetic material in a new generation to expand the search area. [54], [55], [57]

In the first place, a mutation rate must be chosen. In general, the mutation is a quite rare phenomenon in the biology. Consequently, the mutation rate should be a small value. However, it is not possible to find one optimal value of the mutation rate for all optimization problems. Therefore, the set value should be often adapted to the considered task.

The most utilized approach to find the new mutated chromosome variable c_{mut} uses a normal/Gaussian distribution function and is given by [54]:

$$c_{\mathrm{mut}} = c_{\mathrm{old}} + \sigma N\left(0,1\right) \tag{4.29}$$

where c_{old} is the selected chromosome variable for the mutation, σ – the standard deviation of the Gaussian distribution function, $N(0,1)$ – the standard Gaussian distribution with the mean 0 and variance 1.

4.2.2.3 Selection

At the end of each iteration, after the mutation, the strongest individuals of the population are chosen, resp. a new generation is created again. This generation is used for the recombination during the next iteration. The iterative process repeats until the break conditions are fulfilled.

4.2.3 Constraint handling

The bulk of optimization problems not only consist of the objective function, but also of many different linear, non-linear etc. constraints. Therefore, *constraint handling*, i.e. handling of constraint equations in the optimization method, should be integrated in the GAs. However, there is no universal *constraint handling* approach, which could be used in every optimization technique. The *constraint handling* method should be chosen based on the optimization method type and considered optimization problem. [62], [63], [64], [65]

There are various *constraint handling* , which can be used for the GAs. They can be classified in the following groups [62], [65]:

- utilization of penalty functions
- search of feasible solutions
- distinction between feasible and infeasible solutions
- hybrid methods

The *constraint handling* methods, which are based on the *penalty functions*, are mostly used in the GAs because they are quite simple, easily implementable and well-working for many optimization problems. They convert a constrained optimization problem to an unconstrained problem by penalizing unfeasible solutions [62], [63], [64], [65].

$$f(\boldsymbol{x}) = \begin{cases} f(\boldsymbol{x}) & \text{if } \boldsymbol{x} \in F \\ f(\boldsymbol{x}) + penalty(\boldsymbol{x}), & \text{otherwise} \end{cases} \tag{4.30}$$

where *penalty*($\boldsymbol{x}$) is the penalty parameters and F – the feasible area. If the considered optimization problem is a minimization problem and there is no violation of the constraints, *penalty*($\boldsymbol{x}$) is 0. Otherwise, it is a positive value.

In this chapter, the most common *constraint handling* approaches are introduced.

4.2.3.1 Death penalty

The *death penalty* method is the simplest and mostly used approach for handling constraint optimization problems. It sorts out every unfeasible solution from the generation by penalizing the unfeasible solutions in such a way, that this generation can only consist of the feasible solutions. This method works especially well if the feasible area belongs to the sensible search space. However, if the optimization problem is highly constrained, the *death penalty* approach has a high computation time and the proposed best solution might not be accurate enough. [62]

4.2.3.2 Static penalty

The *static penalty* method is also a quite simple approach for handling the constraint optimization problem. It penalizes the unfeasible solutions as well as the *death penalty* method. However, in this approach some levels of the constraint violation with own penalty coefficient must be chosen. The more constraints are violated by the unfeasible solution, the higher the penalty value for this solution. [62], [65]

$$f(\boldsymbol{x}) = f(\boldsymbol{x}) + \sum_{i=1}^{l}\sum_{j=1}^{m} C_{ij} d_j \quad \text{with} \quad \begin{cases} d_j = 1 & \text{if constraint } j \text{ is violated} \\ d_j = 0 & \text{if constraint } j \text{ is fulfilled} \end{cases} \tag{4.31}$$

where C_{ij} is the penalty coefficient, i – the current violation level, j – the current constraint, l – the level number and m – the constraint number.

However, in this approach a high number of parameters, resp. $m(2l+1)$ parameters, must be selected and applied. This makes the utilization of the static penalty method quite difficult. Furthermore, the accuracy of the solutions strongly depends on the chosen values of these parameters. [65]

4.2.3.3 Dynamic Penalty

As opposed to the previous approach, in the *dynamic penalty* method the penalties change over the time, resp. in every iteration step i. The penalizing of the unfeasible solutions is given by:

$$f(\boldsymbol{x}) = f(\boldsymbol{x}) + (Ci)^{\alpha} \sum_{j=1}^{m} d_j$$

$$\text{with} \quad \begin{cases} d_j = 1 & \text{if constraint } j \text{ is violated} \\ d_j = 0 & \text{if constraint } j \text{ is fulfilled} \end{cases} \tag{4.32}$$

where C and α are the user-defined constants with the recommended values: C = 0.5 and α = 1 or 2. [62], [65]

The accuracy of the solutions strongly depends on the chosen values of the parameters α and β. Furthermore, this approach quite often cannot find any feasible solution or finds a solution, which is not accurate enough. [62], [65]

There are many other methods for the *constraint handling*. But they are not described in this chapter because they are not considered in this work.

4.2.4 Performance

The *genetic algorithm* is widely used for solving different optimization problems in various fields, e.g. engineering, robotics, databases, neural networks, chemistry, bioinformatics, transport, investment and game strategies etc., because it has the following advantages [54]- [58]

- It is easily implementable.
- It can be easily adapted for the considered optimization problem.
- It can work with a large number of variables.
- It works with continuous and discrete variables.
- It is very stable.

Nevertheless, it has some disadvantages, which should be considered by choosing the optimization method:

- It is computational intense.
- It can find an optimal solution, which is not accurate enough.
- It has many parameters, which must be selected by the user.

4.2.5 Non-linear redispatch optimization problem for the GA

Firstly, the linear fitness function c of the redispatch optimization problem for the GA should be minimized by the utilization of equation (4.6) as well as for the simplex algorithm.

The main constraint is taking into account the electric network state and node impact on the congested line. However, the electric network state can be described by the non-linear power flow equations, which are not linearized in comparison to the formulation of the redispatch optimization problem for the simplex algorithm.

The power plant potentials, which can be used for the redispatch realization, are considered with the help of equations (4.11) and (4.12) as well.

Furthermore, in the first place, the lowest-cost power plants are used in an ascending order of their total costs to cover the load consumption. This process is called a merit order. However, the merit order data can sometimes include errors, in which the more expensive power plants are used instead of cheaper one. In this case, a profit could be theoretically made by the utilization of the redispatch, which is not possible in the practice. Hence, based on equation (4.8), the redispatch total costs for each power plant pair must be positive:

$$c_{\mathrm{incr},i} - c_{\mathrm{red},j} \geq 0 \tag{4.33}$$

Moreover, the cost objective function c must be equal or greater to 0:

$$c \geq 0 \tag{4.34}$$

In addition, the start-up and shut-down of power plants can be taken into account by an implementation of the so-called integer variables into the redispatch optimization problem. Here, the integer variables can take only binary values 0 or 1.

In this case, the costs c for the realization of redispatch considering the PPCC and PPSDC, which might be minimized, is utilized as the non- linear *fitness function* for the considered optimization problem and is formulated as follows [4], [15], [17], [40]-[42], [44], [66], [67], [68]:

$$c = \sum_{i=1}^{G}\sum_{j=1}^{G}\Delta P_{ij}\Delta c_{ij} + \sum_{i=1}^{G_{\text{su}}} c_{\text{su},i} su_i + \sum_{i=1}^{G_{\text{sd}}} c_{\text{sd},i} sd_i \tag{4.35}$$

where G_{su}, G_{sd} are the number of the power plants, which need to be started-up and shut down, su_i and sd_i are the binary variables, which are 1 if the power plants are started-up and shut down, otherwise they are equal to 0.

If the power plant, which participates in the redispatch, should be started-up, its total generated active power P_i must be equal or less to its maximum active power $P_{\text{max},i}$ and, at the same time, equal or greater to its minimum active power $P_{\text{min},i}$, which are multiplied with the binary status variable su. [66]

$$P_i \leq P_{\text{max},i} su_i \tag{4.36}$$

$$P_i \geq P_{\text{min},i} su_i \tag{4.37}$$

Finally, the PPSDC are neglected in this work because they are very small compared to other cost types (see Table 3.4).

4.2.6 Algorithm adaptation for the non-linear redispatch optimization problem

First of all, the GA is developed and adapted for the described redispatch optimization problem to compare its results with results of the remaining optimization techniques, which are utilized in this work. Furthermore, the GA is tested in a small network model and simplified network model of the ENTSO-e power grid, which are described in detail in chapter 5.1.

There are various ways to implement the GA However, the choice of the genetic algorithm type primarily depends on the formulation of the considered optimization problem. The previously introduced non-linear optimization problem for the redispatch realization consists of continuous variables. Therefore, in this work, the so-called *continuous genetic algorithm*, which is described in detail in chapter 4.2.2 and shown by the flowchart in Figure 4.1, is implemented to solve this task.

In the developed GA, a randomly created initial population consists of the chromosomes, which include the possible power generation changes for all power plant combinations of the considered network models. Here, the positive and negative redispatch potentials of each power plant pair must be taken into account. Furthermore, the population individuals include binary values for the start-up and shut-down status of the power plants. Hovewer, these binary combinations are not random values. They are generated according to the chosen power plant pairs.

To produce new offspring chromosomes, the approach of the one crossover point of two parent chromosomes is used based on equations (4.25) and (4.26). Furthermore, to include a new genetic material in the offspring, new values, which are based on different combinations of the parent variable values, are integrated in the offspring by equation (4.27). Therefore, these new values replace the crossover point as shown in equation (4.28). In every iteration step a new generation is built based on the parent and offspring chromosomes.

The mutation is implemented in the GA to find a local minimum in the search space using equation (4.29). Here, the mutation rate is adaptive and depends on the optimization problem, i.e. on the power plant number and population size.

After the mutation, the strongest population individuals are chosen to create a new generation for the next iteration step. This iterative process repeats until the break conditions are fulfilled.

As already mentioned, the parameters of the *evolutionary algorithms* usually need to be adopted for the considered optimization problem. The developed GA for the introduced non-linear redispatch optimization problem with the consideration of the power flow equations and PPCC is parameterized as follows:

- The population consists of 200 individuals: 100 strongest parent chromosomes and their 100 offspring.
- The mutation rate is 0.4 by reference to the power plant pair number 64 and population size 200.
- The standard deviation of the Gaussian distribution function σ is 0.05.
- The iteration number is 10000. However, if the best solution cannot be improved during many iterations, the iterative process is stopped.
- The static penalty for the constraint handling is 1000000.

4.3 Mean Variance Mapping Optimization

The *Mean Variance Mapping Optimization* (MVMO) is a new stochastic optimization method which is based on the GA. But a novelty in this optimization technique is the utilization of the so-called *mapping function* (MF) for the mutation process. The MF is based on mean and variance of some best solutions, which are saved in a continually updated archive. The MVMO was developed by István Erlich in 2010 motivated by the continually increasing complexity of the power system. Nevertheless, the MVMO has a big potential to be used for solving optimization problems in different areas. [4], [69], [70], [71], [72], [73], [74], [75], [76]

4.3.1 General approach

The MVMO solves optimization problems with the same objective function and constraints as well as the GA, which are already described in equations (4.13) and (4.14).

However, as opposed to the GA, in the MVMO the offspring mutation is based on the MP, resp. on the mean and variance of the best individuals of the population, which are stored in an archive. The MF is usually defined in a range between 0 and 1. Hence, the optimization variables must be scaled correspondingly to this range. In addition, during the iteration process the shape of the MF is constantly modified according to the progress of the best solution search. [4], [69]-[76]

Therefore, the initial individuals x_i are transformed into the new mutated generation $x_{\text{new},i}$ using the MF. This transformation, resp. generation mutation, takes place according to the following equation (4.38) and is shown in Figure 4.2 [4], [69]:

$$x_{\text{new},i} = h_x + (1 - h_1 + h_0)\, x_i - h_0 \tag{4.38}$$

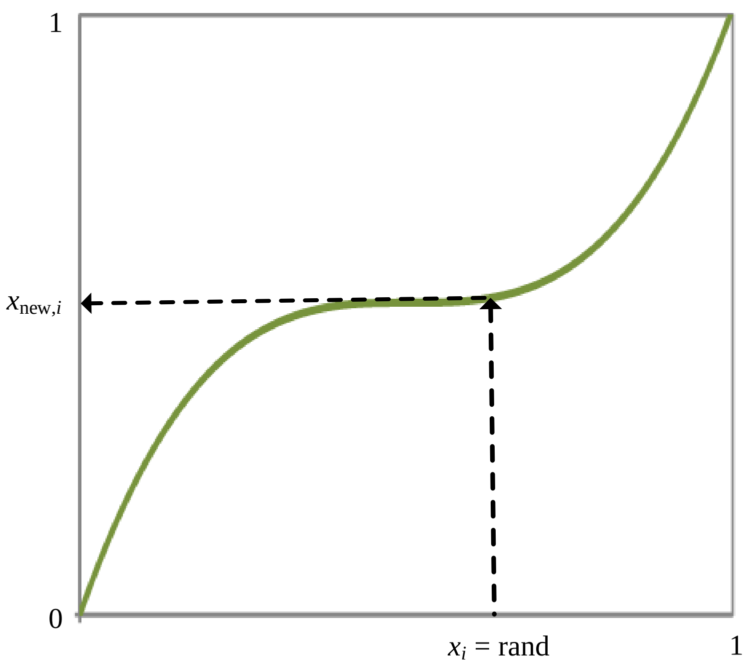

Figure 4.2 Mapping function example [69]

Where the h-function h_x is determined by:

$$h_x = \bar{x}_i \left(1 - \mathrm{e}^{-x_i \cdot s_{i1}}\right) + \left(1 - \bar{x}_i\right) \mathrm{e}^{-(1 - x_i) \cdot s_{i2}} \tag{4.39}$$

The parameters h_1 and h_0 are calculated by x_i=1 and x_i=0 using equation (4.39).

The mean of the variables $\bar{x}_i$ is established based on the archive with the n best solutions as shown below:

$$\bar{x}_i = \frac{1}{n} \sum_{j=1}^{n} x_i(j) \tag{4.40}$$

where x_i is the best solution, which are stored in the archive.

The shape variables s_i are determined using the variance of the variables v_i:

$$s_i = -\ln(v_i)\, f_s \tag{4.41}$$

where f_s is the factor for changing the shape of the MF and calculated by:

$$f_s = f_s^* (1 + rand) \tag{4.42}$$

with the smallest value f_s^* of the shape factor f_s and the random value *rand* which is between 0 and 1.

The variance of the variables v_i is determined based on the archive with the n best solutions x_i as well the mean of the variables:

$$v_i = \frac{1}{n} \sum_{j=1}^{n} \left(x_i(j) - \overline{x}_i \right)^2_{\ i} \tag{4.43}$$

The shape factor f_s is greater than 1 if the calculation accuracy must be increased and it is less than 1 if the search of the solution shall be more global.

If the accurancy of the MVMO should be increased, the factor f_s^* can be calculated as follows:

$$f_s^* = f_{\text{start}}^* + \left(\frac{i}{i_{\max}} \right)^2 \left(f_{\max}^* - f_{\text{start}}^* \right) \tag{4.44}$$

where f_{start}^* is the smallest value of the factor f_s^* and can be chosen between 0.9 and 1, $f_{\max}^*$ is its largest value and can be defined between 1 and 3, i is the current iteration and $i_{\max}$ is the maximum number of the iterations.

The shape variables s_{i1} and s_{i2} can be found using the algorithm, which is shown in Figure 4.3.

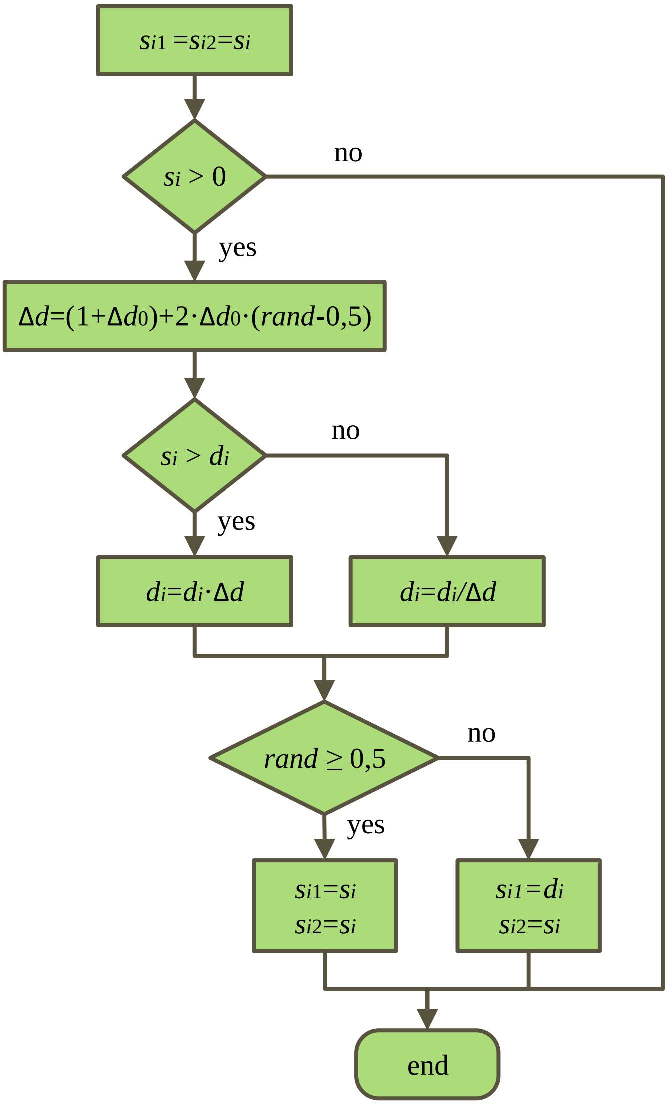

Figure 4.3 Algorithm for the determination of the shape variables

The start value of the variables d_i must be set before the iterative process starts and should be defined between 1 and 1.5 based on the simulation experience [69]. The parameter d_i is used instead of s_{i1} to smooth the h-function.

Basically, if s_i is greater than 0, d_i is continually scaled with the factor Δd. If s_i is greater than d_i, the factor d_i is scaled up with Δd, i.e. d_i becomes larger than at the beginning. Here, the factor d_i remains close to the value of s_i. Otherwise, the factor d_i is scaled down with Δd, i.e. d_i becomes smaller because Δd is always greater than 1.

In addition, the factor Δd oscillates around the value $(1+\Delta d_0)$ with decreasing amplitude Δd_0 as shown below:

$$\Delta d_0 = \Delta d_{0,\mathrm{start}} + \left(\frac{i}{i_{\max}} \right)^2 \left(\Delta d_{0,\max} - \Delta d_{0,\mathrm{start}} \right) \tag{4.45}$$

where $\Delta d_{0,\mathrm{start}}$ is the smallest value of the factor Δd_0 and $\Delta d_{0,\max}$ is its largest value.

The factor Δd_0 should be defined between 0.01 and 0.4 based on the simulation experience [69].

The size of the archive for the MVMO should be small and usually varies between 2 and 5 of the currently best individuals. The utilization of a larger archive can lead to a too strong influence of the best solutions on the orientation of the search.

4.3.2 Performance

The MVMO is a quite new optimization method, which is not yet widely used. In the main, it is successfully utilized for different optimization problems in the power systems. Basically, it has the same advantages and disadvantages as the GA because the MVMO is based on the GA. The only difference is that the MVMO uses the MP for the mutation process. Its most important advantage is the searching for a global solution with the consideration of the best individuals, which makes this optimization method more efficient. Nevertheless, a complicate mathematical description of the mutation process leads to a longer computation time, resp. use of more computer resources. [69]

4.3.3 Non-linear redispatch optimization problem for the MVMO

In this work, the fitness function c of the redispatch optimization problem for the MVMO should be minimized by the utilization of linear and non-linear equations (4.6) and (4.35) in the same way as for the GA.

The main constraint of the redispatch optimization problem is taking into account the electric network state and node impact on the congested line using the network sensitivity analysis by equation (4.9) or the non-linear power flow equations as well as by the GA.

The remaining constraints for the developed MVMO are already formulated by equations (4.11), (4.12), (4.33)-(4.37).

4.3.4 Algorithm adaptation for the non-linear redispatch optimization problem

The MVMO algorithm is developed and adapted for the described redispatch optimization problem to compare its results with the results of the remaining optimization techniques, which are utilized in this work as well as the GA. Furthermore, it is also tested in the already mentioned small network model and simplified network model of the ENTSO-e power grid (see chapter 5.1).

Due to the MVMO is a variation of the GA, producing the chromosomes and their offspring is made in the same way as in the GA (see chapter 4.2.2). The so-called *mapping function* , which is described in detail in chapter 4.3.1, is used during the mutation. Therefore, the population individuals are transformed into a new mutated generation utilising the MF in equation (4.38). To calculate the MF, the h-function, which is based on the mean and variance of in the archive stored best solutions, must be dermenated using equations (4.39)-(4.45).

After the mutation the strongest population individuals are chosen to create a new generation for the next iteration step. This iterative process repeats until the break conditions are fulfilled.

The developed MVMO for the introduced non-linear redispatch optimization problem is parameterized as follows:

- The population consists of 200 individuals: 100 strongest parent chromosomes and their 100 offspring.
- The mutation rate is 0.4 by reference to the power plant pair number 64 and population size 200.
- The archive size is 4.
- The smallest value of the factor f_s^* is 0.9 and its greatest value is 1.5.
- The smallest value of the factor Δd_0 is 0.01 and its greatest value is 0.4.
- The iteration number is 10000. However, if the best solution cannot be improved during many iterations, the iterative process is stopped

- The static penalty for the constraint handling is 1000000.

4.4 Particle Swarm Optimization

The *Particle Swarm Optimization* (PSO) is a heuristic global optimization technique and belongs to the family of the metaheuristic algorithms as well as the GA. This method is based on population principles, resp. on the behavior of swarm individuals, which are moving in the search-space according to a mathematical description of their position and velocity. It was developed by J. Kennedy and R. Eberhart in 1995 inspired by the social behavior of a flock of birds. It is used in a variety of areas, e.g. engineering, telecommunications, bioinformatics, computer science, economy, signal processing, fuzzy logic etc. [4], [77], [78], [79], [80], [81], [82], [83], [84]

4.4.1 General approach

The PSO algorithm solves optimization problems with the same objective function and constraints as well as the GA, which are already mathematically formulated in (4.23) and (4.24).

However, in contrast to the GA, in the PSO the population, resp. swarm, consists of so-called particles, resp. potential solutions of the optimization problem. Each of these particles follows the current best particle, resp. 'flys' through the search space following the current best solution. Thereby, the PSO continuously determines the new position of each particle with in the solution space and own speed of the movement. [4]

The position p and velocity v of the particles are updated in each iteration step according to the following equations and are shown in Figure 4.4:

$$v_{i+1} = \omega_i v_i + c_1 r_1 \left(p_{\mathrm{lb},i} - p_i \right) + c_2 r_2 \left(p_{\mathrm{gb},i} - p_i \right) \tag{4.46}$$

$$p_{i+1} = p_i + v_{i+1} \tag{4.47}$$

where ω_i is the inertia weight factor, which can be defined between 0 and 1, c_1, c_2 are the acceleration coefficients, r_1, r_2 are random numbers between 0 and 1, p_{lb}, p_{gb} are the best positions of the respective particle and the entire group until the current iteration step i and p_i is the current position of the particle in the current iteration i. [4], [77]-[84]

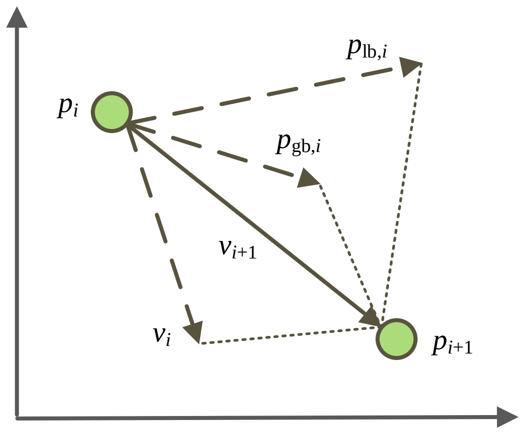

Figure 4.4 Particle movement

At the beginning, before the PSO starts to optimize, an initial population, resp. initial swarm, must be created. The individuals, resp. particles of this swarm, are randomly distributed in the solution space, i.e. their initial position and velocity are randomly set. Moreover, before the population initialization, the objective function, constraints of optimization problem and PSO parameters must be defined. After that the objective function for each individual must be evaluated. Then the best position for each particle and global best position must be updated. Therefore, a new population is formed. The above process repeats until the break conditions, e.g. finding acceptable solution or exhaustion of the iteration steps, are fulfilled. A flowchart of the described iterative process is given in Figure 4.5. [77]-[84]

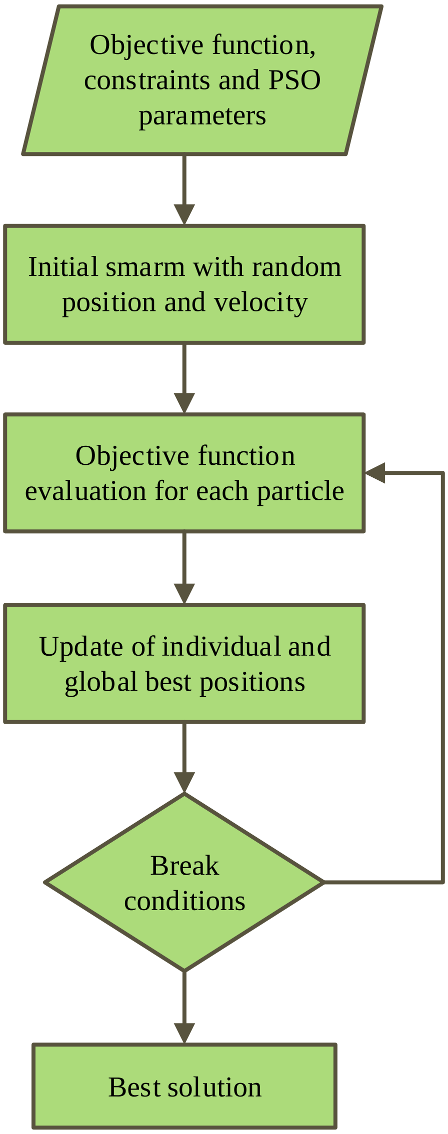

Figure 4.5 Flowchart of particle swarm optimization

4.4.1.1 Inertia weight factor

The *inertia weight* is an important factor for a balance between the exploration and exploitation abilities, which determines the rate between the previous and current velocities of a particle. There are various methods to calculate the inertia weight factor: from simple one, where this factor is a constant value, to complex techniques such as methods of Ackley or Rastrigin [85].

In this work, only the so-called *linear decreasing method* for calculation of the *inertia weight factor* is used for the optimization of the redispatch realization with the PSO. Therefore, it is introduced in this chapter below.

In the *linear decreasing method*, the *inertia weight factor* ω_i is calculated in each iteration step i according to the following equation [85], [86]:

$$\omega_i = \frac{(\omega_{\max} - \omega_{\min})(i_{\max} - i)}{i_{\max}} + \omega_{\min} \tag{4.48}$$

where $\omega_{\max}$ and $\omega_{\min}$ are the maximum and minimum values of the inertia weight factor and $i_{\max}$ is the maximum number of iterations.

Therefore, in this method, the inertia weight factor increases linearly during the simulation. Thereby, its small values are more suitable for the local search and its large values – for the global search.

4.4.1.2 Recommended parameter values

Before the iterative simulation all parameters of the PSO algorithm must be set. The values of these parameters have a strong influence on the PSO algorithm accuracy. Hence, they must be carefully chosen. Nevertheless, this is not a trivial task because these values vary very strongly. However, there are some recommended parameter values, which generally provide good results for different optimization problems. Therefore, the maximum value of the inertia weight factor $\omega_{\max}$ is usually 0.9 and its minimum value $\omega_{\min}$ is 0.4, and the values of the acceleration coefficients c_1, c_2 are 2. [77]-[86]

4.4.2 Performance

Nowadays, the PSO is used in various fields to solve different optimization problems. There are several main advantages, which make the PSO extremely attractive for the users [87]:

- It is based on a simple calculation method and is easily understandable.
- It is easy to implement.
- It has a low computation time.
- It is very flexible.

Nevertheless, the PSO has some disadvantages, which should be also considered by choosing the optimization method:

- Its convergence cannot be ensured by a finite number of the particles. Hence, the calculation of the objective function must be realized several times.
- Focus on the best particle can lead to breaking the PSO if a satisfying solution is found instead of the global optimum.

4.4.3 Non-linear redispatch optimization problem for the PSO

The fitness function *c* of the redispatch optimization problem for the PSO should be minimized by the utilization of linear and non-linear equations (4.6) and (4.35) in the same way as for the already described metaheuristic optimization methodologies.

The constraints, which are used in the redispatch optimization problem are already described in chapter 4.2.5.

4.4.4 Algorithm adaptation for the non-linear redispatch optimization problem

The PSO is developed and adapted for the described redispatch optimization problem to compare its results with the results of the remaining optimization techniques, which are used in this work. Furthermore, it is also tested in the already mentioned small network model and simplified network model of the ENTSO-e power grid (see chapter 5.1).

The particles of the PSO include the possible power generation changes for all power plant combinations of the considered network model and binary values for the start-up and shut-down status of the power plants. Here, the positive and negative redispatch potentials of each power plant pair must be considered as well as by using the GA or

MVMO. The position and velocity of the particles are updated in each iteration step according to equations (4.46)-(4.48). This iterative process repeats until the break conditions are fulfilled. The developed PSO is described in detail in chapter 4.4.1.

The developed PSO for the introduced linear and non-linear redispatch optimization problem is parameterized as follows:

- The swarm consists of 200 individuals.
- The acceleration coefficients c_1=c_2 are 2.
- The maximum and minimum values of the inertia weight factor ω_{max} and ω_{min} are 0.9 and 0.4.
- The iteration number is 3000. However, if the best solution cannot be improved during many iterations, the iterative process is stopped.
- The maximum number of runs is 10.
- The static penalty for the constraint handling is 1000000.

4.5 Ant Colony Optimization

The *Ant Colony Optimization* (ACO) is a heuristic optimization technique and belongs to the family of the metaheuristic algorithms as well as the GA. This method is based on the so-called swarm intelligence of fishes, birds, insects etc. as well as the PSO. The ACO was developed by M. Dorigo in the early 1990's inspired by the foraging behavior of a real ant colony. It is utilized in a variety of areas, e.g. engineering, telecommunications, computer science, economy, deployment planning, for multicriteria optimization problems etc. [88], [89], [90], [91], [92], [93], [94], [95]

4.5.1 General approach

The ACO solves optimization problems with the same objective function and constraints as well as the GAs, which are already described in equations (4.23) and (4.24).

In the ACO the population, resp. a colony, consists of ants, resp. potential solutions of the optimization problem. The ant colony searches a shortest way between its nest and a food source. During searching every ant leaves a trail on the ground by means of chemical pheromones. The pheromones serve for guiding other ants to the food source. The stronger the pheromone concentration on the way, the higher the probability, that the ants will choose this way. This behavior of the ant colony is shown in Figure 4.6 [88]- [90], [92]:

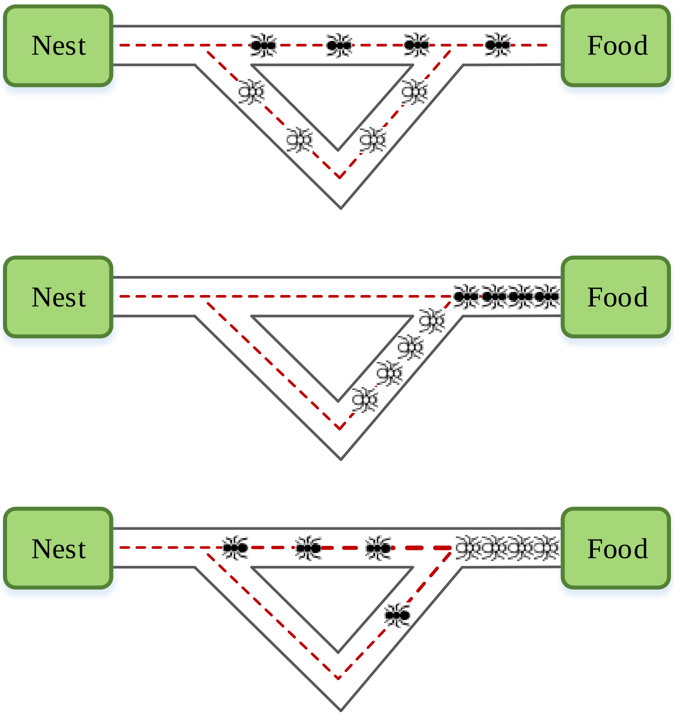

Figure 4.6 Food searching of an ant colony [88], [89], [92]

In Figure 4.6 the ants are searching for a food source. Initially, one half of the colony (black ants) chooses the shortest way to the food and the other half (white ants) – the longest one. Therefore, the black ants reached the destination earlier than the white ones. Consequently, the probability that they take the shortest route to come back to their nest is much higher. Over time, the pheromone concentration on the shortest way gets much stronger than on the longest one till the whole ant colony chooses only the shortest route.

The already mentioned probability $p_{k,ij}(t)$ in the iteration step t can be calculated as follows [88], [89], [93], [94]:

$$\begin{cases} p_{k,ij}(t) = \dfrac{\left(\tau_{ij}(t)\right)^{\alpha}\left(\eta_{ij}\right)^{\beta}}{\sum\limits_{l \in J_{k,i}} \left(\tau_{il}(t)\right)^{\alpha}\left(\eta_{il}\right)^{\beta}}, & j \in J_{k,i} \\ p_{k,ij}(t) = 0, \quad j \notin J_{k,i} \end{cases} \tag{4.49}$$

where the ant k, which is currently on the node i, considers all neighboring nodes j as potential routes. $\tau_{ij}(t)$ are the pheromone trails, which an ant leaves on the ground.

η_{ij} are the heuristic values or optional weighting function, which can be determined as given [93]:

$$\eta_{ij} = \frac{1}{d_{ij}} \tag{4.50}$$

where d_{ij} is the distance between the nodes i and j.

α and β are the constant values, which reflect the relation between the pheromone trails and heuristic values. If α approaches zero, the nearest j node is chosen. If β approaches zero, the selection of the neighboring node is based only on the pheromone trails, i.e. the distances between the node i and nodes j are not completely taken into account. [88], [89]

$J_{k,i}$ is the feasible solutions, resp. neighboring nodes of the node i for the ant k, i.e. the neighboring nodes l, which were not yet visited by the ant k [93].

The pheromone quantity $\Delta\tau_{k,ij}(t)$, which is secreted on the distance between the nodes i and j by the ant k, is determined by [93]:

$$\Delta\tau_{k,ij}(t) = \begin{cases} \dfrac{Q}{L_k(t)}, & (i,j) \in R_k(t) \\ 0, & (i,j) \notin R_k(t) \end{cases} \tag{4.51}$$

where $L_k(t)$ is the length of the route $R_k(t)$, which is traveled by the ant k in the iteration t, Q is the optional weighting of the length of the optimal route.

Taking into account the pheromone evaporation ρ the pheromone trails can be calculated as given by [93]:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t) \tag{4.52}$$

subject to:

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{n} \Delta\tau_{k,ij}(t) \tag{4.53}$$

where n is the number of the ants in the colony.

The pheromone evaporation ρ is defined between 0 and 1. Its initial value must be very small and positive. [93]

Based on the simulation experience [88], the constant α and β should be set to 1 and 5, the pheromone evaporation ρ – to 0.5.

The ACO was originally developed for discrete optimization problems such as the famous traveling salesman problem (TSP). In the TSP a salesman must visit a certain number of cities only once and at the same time the traveling distance must be minimal. Nevertheless, there are some modifications of the ACO to solve optimization problems in continuous domains. [88], [89], [95]

4.5.1.1 Ant Colony Optimization algorithm for continuous domain

As already mentioned, there is a large quantity of optimization problems, which are considered in the continuous domain i.e. the solution variables are continuous. Therefore, different modifications of the ACO for the continuos domain, such as a continuous ant colony optimization, continuous interacting ant colony, pachycondyla apicalis ant optimization etc., were developed in the resent years. However, many of these methods do not follow the original conditions of the ACO. [91]

Nevertheless, there is an often-used optimization technique, the so-called ACOR algorithm, which is very close to the original ACO. To handle the continuous optimization problem, the ACOR uses a solution archive to save the search process history. For the probability distribution of the solutions the so-called *probability density functions* (PDF) is utilized by this optimization method.

An often-applied PDF is a *normal distribution* or *Gaussian distribution function*. However, a single *Gaussian function* has only one maximum. Therefore, it cannot be used for the search space with various areas. To handle this problem an extended Gaussian kernel, PDF $G_i(s)$ with i dimensions can be applied, which is defined as a sum of the single Gaussian functions $g_{il}(s)$ [91], [92]:

$$G_i(s) = \sum_{l=1}^{k} \omega_l g_{il}(s) = \sum_{l=1}^{k} \omega_l \frac{1}{\sigma_i \sqrt{2\pi}} \mathrm{e}^{-\frac{(s_{il}-\mu_{il})^2}{2\sigma_{il}^2}} \tag{4.54}$$

where ω_l is the weighting vector, μ_{il} – the mean vector, σ_l – the variance vector, l is the solution index and k is the number of the solutions.

At each iteration step the ants choose the solution values based on the Gaussian kernel PDF, which are derived from solutions stored in the archive. In this way, the initial solutions are improved during the simulation. This approach replaces the calculation of the pheromone trails of the discreet ACO.

The weighting vector ω_l for the solutions s_l is calculated as follows [91]:

$$\omega_l = \frac{1}{qk\sqrt{2\pi}} e^{-\frac{(l-1)^2}{2q^2k^2}} \tag{4.55}$$

where q is the parameter of the solution selection and defined between 0 and 1. Here, the smallest value of the parameter q (~ 0) must be assigned to the best-sorted solution.

The selection probability is determined as shown below [91]:

$$p_l = \frac{\omega_l}{\sum_{l=1}^{k} \omega_l} \tag{4.56}$$

The variance or standard deviation σ_i of the Gaussian functions for the i dimension is calculated by [91], [95]:

$$\sigma_i = \xi \sum_{l=1}^{k} \frac{\left| s_{il} - s_{\mathrm{best},i} \right|}{k-1} \tag{4.57}$$

where ξ is the factor, which is similar to the pheromone evaporation ρ of the discrete ACO and greater than 0. The lower the value of the factor ξ, the higher the convergence speed of the ACOR. $s_{\mathrm{best},i}$ is the best solution for the i dimension.

4.5.1.2 Ant Colony Optimization algorithm with the Prospect Theory for continuous domain

Another often used modification of the ACO for the continuous domain is the so-called *Ant Colony Optimization with the Prospect Theory* (ACOR-PT). In contrast to the ACOR, the search of the optimal solution by the ACOR-PT is based on the *prospect theory* (PT) instead of the *Gaussian distribution function*. The PT describes making human decisions in high-risk situations such as lotteries. This theory was introduced by D. Kahneman and A. Tversky in 1979. [96]

In the ACOR-PT, the solutions are chosen not only based on the probability weighting function, but also on an objective function of the optimization problem. For this purpose, the mean of the objective function of all solutions stored in the archive, the so-called reference point, is determined using equation (4.40). It determines whether the established solutions for the objective function belong to gains or losses. Based on this reference point, a value function for the gains or losses can be built as shown in Figure 4.7.

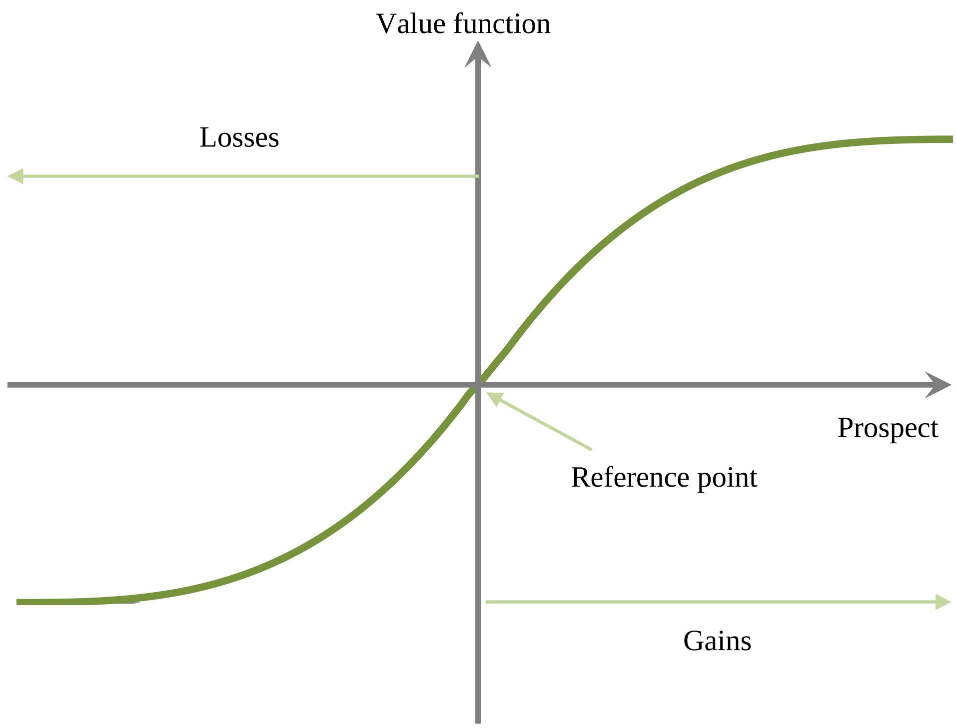

Figure 4.7 Value function [92]

If the calculated solution is greater than the reference point, it is in the gain area. If the solution is less than the reference point, it is in the loss area.

The value function $v(s_l)$ of the PT is determined as shown in equation (4.58):

$$v(s_l)=\begin{cases} s_l^{\alpha}, & s_l \geq 0 \\ -\lambda(-s_l)^{\beta}, & s_l < 0 \end{cases} \tag{4.58}$$

where α, β, λ are the constant parameters, which are greater than 0 and must be defined dependent on the optimization problem. The general recommendation for the parameter values in the literature [92], [97] is $\alpha=\beta=0.88$ and $\lambda=2.25$.

In the ACOR-PT the best solution is determined using the probability weighting function $\omega(p_l)$, which is calculated according to the following equation:

$$\omega(p_l)=\frac{p_l^{\gamma}}{(p_l^{\gamma}+(1-p_l)^{\gamma})^{\frac{1}{\gamma}}} \tag{4.59}$$

where γ is the weighting parameter, which is defined between 0.61 and 0.69 [97].

The probability p_l is calculated utilizing equation (4.56) but with the only difference that k is the number of the solutions, which are stored in the archive. In addition, the weighting vector ω_l is determined using equation (4.55).

Based on the value function $v(s_l)$ and probability weighting function $\omega(p_l)$, the so-called probabilistic prospect $V(s_l)$ for choosing the solution s_l is established by:

$$V(s_l)=v(s_l)\omega(p_l) \tag{4.60}$$

In the ACOR-PT the best solution must have the greatest prospect value. This best solution is used to create a new ant colony in each iteration step as follows:

$$s_l=s_{\text{best}}+\sigma N_l\left(0,1\right) \tag{4.61}$$

where $N_l(0,1)$ is the standard Gaussian distribution with the mean 0 and variance 1.

4.5.2 Performance

The ACO is a quite new optimization technique, which was developed in the early 1990's. Nevertheless, it is already utilized in many different fields for solving optimization problems. There are some main advantages, which make the ACO attractive for the users [92], [94]:

- It finds an effective solution in a very large solution space.
- It is very flexible also by dynamic and complex optimization problems.
- It can be used for broad applications.
- It usually has a low computation time.

Nevertheless, the ACO has some disadvantages, which should be considered by choosing an optimization method:

- Its result is strongly dependent on the choice of its parameter values.
- Its convergence is ensured. However, the computation time sometimes can be long.
- It sometimes needs additional methods to find a local minimum.

4.5.3 Non-linear redispatch optimization problem for the ACO

The fitness function and constraints of the redispatch optimization problem for the ACO are already described in detail in chapter 4.2.5.

4.5.4 Algorithm adaptation for the non-linear redispatch optimization problem

The ACO is developed and adapted for the introduced redispatch optimization problem to compare its results with the results of the remaining optimization techniques, which are utilized in this work. In addition, it is also tested in the small network model and simplified network model of the ENTSO-E power grid (see chapter 5.1).

The ants of the ACO consist of possible power generation changes for all power plant combinations and binary status values for the start-up and shut-down. Furthermore, the positive and negative redispatch potentials of each power plant pair must be considered as well as by using the GA, MVMO or PSO.

To solve the previously introduced optimization problem for the redispatch realization the ACOR-PT is chosen in this work.

At the beginning of the simulation, the initial colony is randomly created. Then the weighting vector, selection probability and probability weighting function are calculated using equations (4.55), (4.56) and (4.59). After that the reference point, which is the mean of the objective function, is determined by equation (4.40). It is utilized to calculate the value function and probabilistic prospect by equations (4.58) and (4.60). The best solution has the greatest probabilistic prospect value. It is used to calculate the standard deviation of the Gaussian functions and create a new ant colony in each iteration step resp. by equations (4.56) and (4.61). This iterative process repeats until the break conditions are fulfilled. The developed ACOR-PT is described in detail in chapter 4.5.1.2.

The developed ACOR-PT for the considered redispatch optimization problem is parameterized as follows:

- The ant colony consists of 400 individuals, which include 150 additional active ants.
- The parameter of the solution selection q is 0.5.
- The weighting parameter γ is 0.68.
- The constant parameters α=β and λ resp. are equal to 0.88 and 2.0.
- The factor ξ is 0.875.
- The iteration number is 1000. However, if the best solution cannot be improved many iterations, the iterative process is stopped.
- The maximum number of runs is 10.
- The static penalty for the constraint handling is 1000000.

5 Case study

The optimization techniques for the redispatch optimization problem, which are introduced in chapter 4, are programmed in the MATLAB computing environment. The developed algorithms are able to find the optimal solutions for the cost objective functions by equation (4.6) and (4.35) taking into account the previously formulated linear and non-linear constraints for redispatch realization by equation (4.9), (4.11), (4.12), (4.33), (4.34), (4.36), (4.37).

5.1 Test network models

The MATLAB routines are tested with the help of a simple small network model and simplified network model of the ENTSO-E power grid.

5.1.1 Small network model

The small test network model, which is utilized to verify the introduced optimization methods, is shown in Figure 5.1 and consists of the following elements:

- 8 bus bars
- 8 power plants
- 10 power lines
- load on bus bar ‘N6’

All power lines have the same parameters to simplify the verification of the simulation results.

Therefore, this test grid model allows to easily understand and manually verify the optimal solutions of the cost optimization problems, which are suggested by the considered optimization techniques.

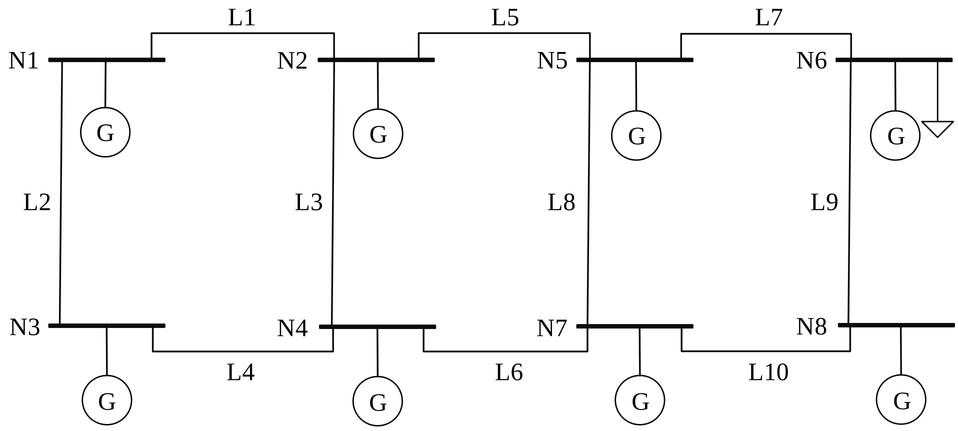

Figure 5.1 Small test network model

To analyze the effectiveness of the developed optimization algorithms, an average cost scenario for the *power plant cycling costs* and *levelized costs of electricity*, which is based on the data from Table 3.1, Table 3.2 and Table 3.3, and the congestions on line 'L5' and 'L7' in the small test network model are chosen for this work. The costs for realization of the active power changes and sensitivity coefficients of lines 'L5' and 'L7' are introduced in Table 5.1.

Table 5.1 Average cost scenario and sensitivity coefficients of lines 'L2' and 'L5'

Power plant bus bar	***N1***	***N2***	***N3***	***N4***	***N5***	***N6***	***N7***	***N8***
Costs in €/MWh	50	80	50	100	220	190	120	50
Sensitivity coefficients of the line 'L5'	0.588	0.66	0.5017	0.445	-0.055	0.017	0.16	0.088
Sensitivity coefficients of the line 'L7'	0.653	0.663	0.635	0.611	0.721	-0.054	0.527	0.245

5.1.2 Simplified ENTSO-E network model

As already mentioned, a simplified grid model of the ENTSO-E area is used to verify the developed optimization methodologies. This model is based on the results of the 'DynaGridCenter' research project funded by the Federal Ministry for Economic Affairs and Energy in Germany [98]. In this project, the developed test network model represents the entire ENTSO-E transmission system. Furthermore, it is based on a cluster model, which is generated within the EU e-Highway2050 project [99]. Here, EU areas with similar characteristics such as the population or installed wind power are combined in clusters (Figure 5.2).

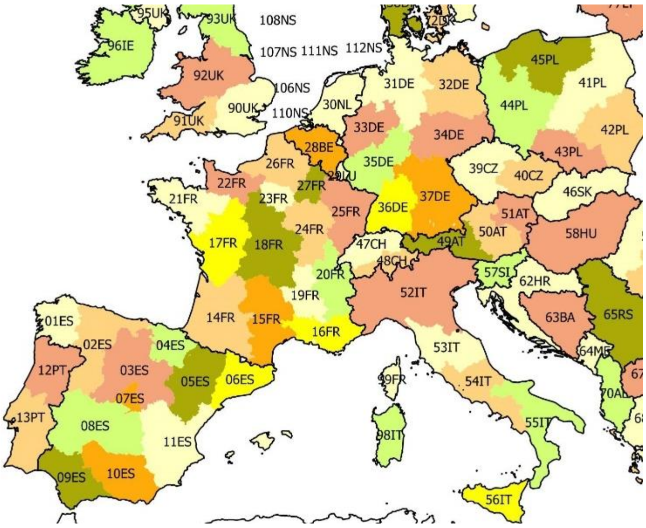

Figure 5.2 Cluster model of the e-Highway2050 project **[99]**

Due to the strong integration of the renewable energy sources (RES) in Germany and its central location, the German transmission network is modeled more detailed in the 'DynaGridCenter' project. Therefore, each cluster in Germany is represented by 3 bus bars, i.e. the German transmission system consists of 21 bus bars. Other countries or areas are modeled by only one bus bar.

Hence, the developed network model includes in total 34 bus bars: 21 bus bars for Germany and 13 for the remaining ENTSO-E areas. These bus bars are connected by 168 transmission lines of the 380 kV voltage level. A network topology of the grid model is shown in Figure 5.3.

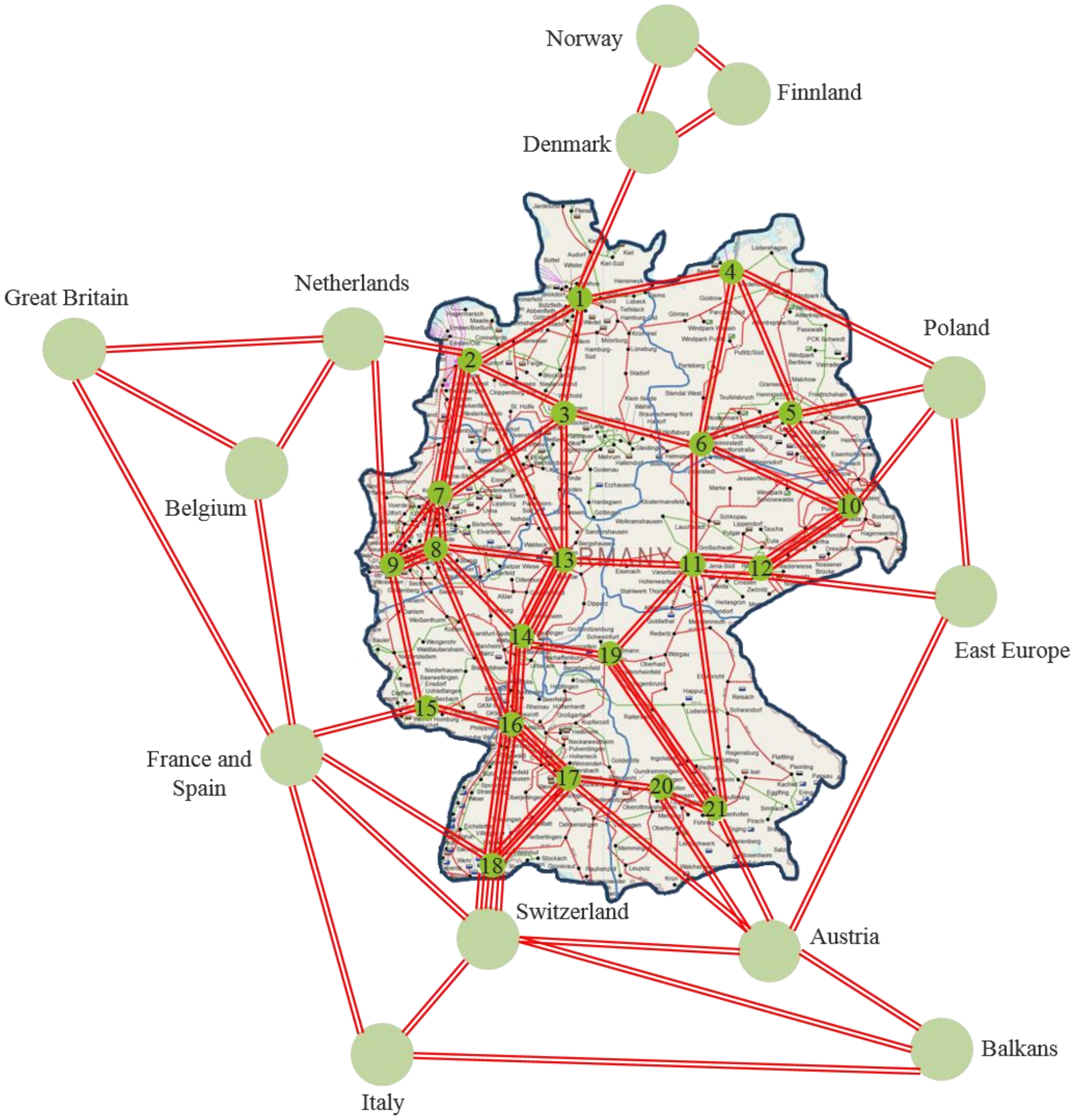

Figure 5.3 Simplified ENTSO-E network model [98]

Furthermore, the conventional power plant, RES, which are modeled by a positive load, and consumption are connected to each bus bar in the power grid model (Figure 5.4).

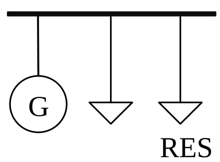

Figure 5.4 Bus bar model [98]

5.2 Redispatch optimization without considering the power plant cycling costs

First of all, the optimization methodologies are verified in the previously introduced small network model and simplified network model of the ENTSO-E power grid. Here, the simplex solves the linear redispatch optimization problem without taking into account the PPCC, which is described in detail in chapter 4.1.2. The metaheuristic methods solve the same optimization problem, however, with the non-linear power flow equations, which is described in chapter 4.2.5.

5.2.1 Simulation results in the small network model

Firstly, all optimization techniques developed in this work are tested in the simple small network model, which is described in detail in chapter 5.1.1 and shown on Figure 5.1.

5.2.1.1 Single network line congestion

In the small network model there are a load of 2500 MW at bus bar ‘N6’ and a power plant at each bus bar with a rated active power of 500 MW. All power plants can be completely shut down, i.e. the power generation in this case is equal to 0.

According to the merit order the power plants at bus bars ‘N1’, ‘N2’, ‘N3’, ‘N4’ and ‘N8’ are working with their rated power to cover the load consumption. Hence, there is still a redispatch potential of maximum 1500 MW in the network model.

Furthermore, in this work, different cost scenarios are created based on the data from Table 3.1. Here, a variety of the LCOE for real conventional power plant types, from smallest to greatest values, are used.

To analyze the effectiveness of the developed optimization algorithms for the redispatch optimization without considering the PPCC, an average cost scenario and the single congestion of 346.5 MW on line ‘L5’ are chosen (see Table 5.1).

If the constraints for the considered optimization problem include the sensitivity coefficients of line ‘L5’, rated active powers of all power plants and their positive and negative redispatch potentials, this optimization problem is becoming linear. Therefore, it can be solved by the simplex algorithm, which could be faster than the metaheuristic methods.

Table 5.2 represents the simulation results of the developed optimization methods for the already mentioned single congestion of 346.5 MW on line ‘L5’ taking into account only the linear constraints without considering the PPCC. Moreover, the simulation time is mean value, which is based on the computation time from twenty simulations for each optimization method.

Table 5.2 Simulation results for the single congestion of 346.5 MW on line ‘L5’ taking into account only the linear constraints

Simulation results	***Optimization methods***				
	Simplex	*GA*	*MVMO*	*PSO*	*ACO*
Simulation time in s	0.011	2.59	10.386	3.392	3.24
Congestion power deviation on line ‘L5’ in MW	4.2	4.2	4.2	4.2	4.2
Power plants (start-up)	6 and 7	6 and 7	6 and 7	6 and 7	6 and 7
Power plants (drive down)	2 and 4	2 and 4	2 and 4	2 and 4	2 and 4
Active power changes in MW for start-up	208.37 and 500	208.37 and 500	208.37 and 500	208.37 and 500	208.37 and 500
Active power changes in MW for driving down	500 and 208.37	500 and 208.37	500 and 208.37	500 and 208.37	500 and 208.37
Total costs in €/h	38753.39	38753.39	38753.39	38753.39	38753.39

In this case, all considered optimization algorithms provide identical results. As expected, the simulation time of the simplex is the shortest one in comparison to the introduced metaheuristic methods. Furthermore, the MVMO needs significantly more computation time. Nevertheless, based on the simulation results, the GA, PSO and ACO solve the redispatch optimization problem fast enough.

In this scenario, only the power plants at bus bars ‘N5’, ‘N6’ and ‘N7’ can be started-up. Furthermore, the power plants at bus bars ‘N1’, ‘N2’, ‘N3’, ‘N4’ and ‘N8’ can be driven down. Here, the best optimal solution is the utilization of the power plants at bus bars ‘N2’, ‘N4’, ‘N6’ and ‘N7’ due to their high sensitivity coefficients and the less total costs for the redispatch realization. Firstly, the capacity of the power plants at bus bars ‘N2‘ and ‘N7’ is completely exhausted. However, the power plants at bus bars ‘N4’ and ‘N6’ need to be utilized as well because the capacity of the first power plant pair is not enough to remedy the occurred line congestion.

However, the linearization of the power flow function can lead to some deviations in the line congestion calculations, especially in the highly loaded power grids. In this scenario, there is a deviation of the congestion power calculation of 4.2 MW. Therefore, in the next step, the SS, which is described in detail in chapter 4.1.3, is used to remedy this congestion deviation. Based on the simulation results, the deviation of 4.2 MW is completely remedied and an average simulation time of the SS is only 0.324 s.

In addition, the non-linear power flow equations are included into the previously introduced linear optimization problem instead of the network sensitivity analysis.

Table 5.3 represents the simulation result for the same congestion on line ‘L5’ but using the non-linear load flow function for the redispatch problem constraints.

Table 5.3 Simulation results for the single congestion of 346.5 MW on line ‘L5’ taking into account the non-linear load flow function

Simulation results	***Optimization methods***			
	GA	*MVMO*	*PSO*	*ACO*
Simulation time in s	391.48	442.38	378.41	338.43
Power plants (start-up)	6 and 7	6 and 7	6 and 7	6 and 7
Power plants (drive down)	2 and 4	2 and 4	2 and 4	2 and 4
Active power changes in MW for start-up	199.17 and 500	199.17 and 500	199.17 and 500	199.17 and 500
Active power changes in MW for driving down	500 and 199.17	500 and 199.17	500 and 199.17	500 and 199.17
Total costs in €/h	37925.30	38753.30	38753.30	38753.30

Here, all introduced metaheuristic methodologies have a large computation time. The optimal solution is using the same power plants as well. However, the needed power generation changes, resp. the total costs, are less than in the first scenario. Hence, in the previous test case there is a deviation of 2.18% or 828.09€/h from the optimal total costs of 37925.30 €/h.

5.2.1.2 Multiple network line congestion

Furthermore, the developed optimization algorithms are verified through the simulation of multiple network line congestions in the small grid model. The initial conditions of this test network model are described in chapter 5.2.1.1. In addition, an average cost scenario, which is already used in chapter 5.2.1.1, and the multiple congestion of 346.5 MW and 300 MW on lines ‘L5’ and ‘L7’ are considered (see Table 5.1).

Table 5.4 represents the simulation results of the developed optimization methods for the multiple line congestion taking into account only the linear constraints for the redispatching.

Table 5.4 Simulation results for the multiple congestion on lines ‘L5’ and ‘L7’ taking into account only the linear constraints

Simulation results	***Optimization methods***				
	Simplex	*GA*	*MVMO*	*PSO*	*ACO*
Simulation time in s	0.018	4.09	9.46	3.70	3.11
Congestion power deviation on line ‘L5’ in MW	6.3	6.3	6.3	6.3	6.3
Congestion power deviation on line ‘L7’ in MW	18	18	18	18	18
Power plants (start-up)	6 and 7	6 and 7	6 and 7	6 and 7	6 and 7
Power plants (drive down)	2 and 4	2 and 4	2 and 4	2 and 4	2 and 4
Active power changes in MW for start-up	378.20 and 402.38	378.20 and 402.38	378.20 and 402.38	378.20 and 402.38	378.20 and 402.38
Active power changes in MW for driving down	280.58 and 500	280.58 and 500	280.58 and 500	280.58 and 500	280.58 and 500
Total costs in €/h	47697.58	47697.58	47697.58	47697.58	47697.58

In this scenario, all optimization methods provide identical results as well as in the previous test case. As expected, the simplex has the shortest computation time.

Here, the best optimal solution is the utilization of the power plants at bus bars ‘N2’, ‘N4’, ‘N6’ and ‘N7’ due to their high sensitivity coefficients and the less total costs for the redispatch realization.

Furthermore, there are deviations of the congestion power calculation of 6 MW and 18 MW on lines ‘L5’ and ‘L7’. Therefore, the non-linear power flow function is included into the linear optimization problem instead of the network sensitivity analysis.

Table 5.5 represents the simulation results for the multiple line congestion using the non-linear power flow equations for the constraints of the redispatch problem.

Table 5.5 Simulation results for the multiple congestion on lines ‘L5’ and ‘L7’ taking into account the non-linear load flow function

Simulation results	*Optimization methods*			
	GA	*MVMO*	*PSO*	*ACO*
Simulation time in s	457.56	517.09	394.87	363.58
Power plants (start-up)	6 and 7	6 and 7	6 and 7	6 and 7
Power plants (drive down)	2 and 4	2 and 4	2 and 4	2 and 4
Active power changes in MW for start-up	416.15 and 339.97	416.15 and 339.97	416.15 and 339.97	416.15 and 339.97
Active power changes in MW for driving down	256.21 and 500	256.21 and 500	256.21 and 500	256.21 and 500
Total costs in €/h	49378.91	49378.91	49378.91	49378.91

In this scenario, the metaheuristic methods have again a large computation time. The optimal solution is using the same power plants as well as in the linear redispatch optimization problem. However, to remedy the multiple line congestion completely, the power generation changes, resp. the total costs, must be greater than it is calculated in the previous test case. Moreover, there is a deviation of 3.4% or 1681.33€/h from the optimal solution with the total costs of 49378.91€/h.

5.2.2 Simulation results in the simplified ENTSO-E network model

The considered optimization methodologies are also verified through simulations of multiple network line congestions in the network model of the ENTSO-E area as well, which is described in detail in chapter 5.1.2 and shown on Figure 5.3.

5.2.2.1 Multiple network line congestion

In this case study, the redispatch can be realized by the utilization of the power plants in the entire ENTSO-E area. This area is represented by 34 bus bars. There is a power plant on each node. Furthermore, there is a power transit of 6 GW from north to south of Germany. According to the merit order the power plants at bus bars ‘1’, ‘2’, ‘4’, ‘5’, ‘7’, ‘9’, ‘11’, ‘12’, ‘13’, ‘14’, ‘15’, ‘17’, ‘18’, ‘20’ and ‘21’ (see Figure 5.3) are working with their rated power to cover the load consumption in Germany. These power plants can be completely shut down, i.e. their power generation is equal to 0.

The positive and negative redispatch potentials of the power plants in Germany, which are used in this scenario, are shown in Table 5.6. The remaining power plants in other countries have the positive redispatch potentials of 2000 MW and costs for the redispatch realization of 110 €/MWh each.

Table 5.6 Positive and negative redispatch potentials in Germany

Power plant bus bar	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***
Positive redispatch potential in GW	0	0	1.2	0	0	1.2	0	2	0	0.5
Negative redispatch potential in GW	2.8	2.8	0	3	3	0	5.3	0	1	1
Power plant bus bar	***12***	***13***	***14***	***15***	***16***	***17***	***18***	***19***	***20***	***21***
Positive redispatch potential in GW	0	0	0	0	0.4	0	0	0.8	0	0
Negative redispatch potential in GW	1	1	1	1	0	1	1	0	1.8	1.8

In this work, different cost scenarios are created based on the data from Table 3.1. Here, a variety of the *levelized costs of electricity* for real conventional power plant types, from minimum to maximum value, are used. To analyze the effectiveness of the developed optimization techniques, the average cost scenario, which is shown in Table 5.7, and the multiple congestion of 104 MW, 118 MW and 63 MW resp. on the double power lines between bus bars '1' and '2', '1' and '3', '11' and '19' are chosen. Therefore, the constraints for the linear redispatch optimization problem include the sensitivity coefficients of these three power lines (Table 7.1), rated active powers of all power plants and their positive and negative redispatch potentials (Table 5.6).

Table 5.7 Average cost scenario

Power plant bus bar	***1***	***2***	***3***	***4***	***5***	***6***	***7***
Costs in €/MWh	50	55	110	50	60	120	50
Power plant bus bar	***8***	***9***	***10***	***11***	***12***	***13***	***14***
Costs in €/MWh	140	50	110	80	70	60	50
Power plant bus bar	***15***	***16***	***17***	***18***	***19***	***20***	***21***
Costs in €/MWh	45	130	90	65	155	85	60

Table 5.8 represents the simulation results of the developed optimization techniques for the already described multiple line congestion taking into account only the linear constraints without considering the PPCC.

Table 5.8 Simulation results for the multiple congestion on line between bus bars ‘1’ and ‘2’, ‘1’ and ‘3’, ‘11’ and ‘19’ taking into account only the linear constraints

Simulation results	***Optimization methods***				
	Simplex	*GA*	*MVMO*	*PSO*	*ACO*
Simulation time in s	0.047	102.42	178.57	157.24	105.75
Congestion power deviation on line between ‘1’ and ‘2’in MW	3.1	3.1	3.1	3.1	3.1
Congestion power deviation on line between ‘1’ and ‘3’in MW	6.4	6.4	6.4	6.4	6.4
Congestion power deviation on line between ‘11’ and ‘19’	4.5	4.5	4.5	4.5	4.5
Power plants (start-up)	3, 16 and 19	3, 16 and 19	3, 16 and 19	3, 16 and 19	3, 16 and 19
Power plants (drive down)	1	1	1	1	1
Active power changes in MW for start-up	178.74, 292.03 and 133.93	178.74, 292.03 and 133.93	178.74, 292.03 and 133.93	178.74, 292.03 and 133.93	178.74, 292.03 and 133.93
Active power changes in MW for driving down	604.69	604.69	604.69	604.69	604.69
Total costs in €/h	48148.89	48148.89	48148.89	48148.89	48148.89

The optimization methodologies provide identical results as well as in the previous scenarios. The simplex method also has the shortest computation time compare to the metaheuristic techniques.

In this test case, the best optimal solution is the utilization of the power plants at bus bars ‘1’, ‚3‘, ‘16’ and ‘19’ due to their high sensitivity coefficients and less total costs for the redispatch realization.

In addition, there are deviations of the congestion power calculation of 3.1 MW, 6.4 MW and 4.5 MW on lines between bus bars ‘1’ and ‘2’, ‘1’ and ‘3’, ‘11’ and ‘19’. Therefore, in the next step, the non-linear power flow equations are included into the previously introduced linear optimization problem instead of the network sensitivity analysis as well.

Table 5.9 represents the simulation result for the mentioned multiple line congestion but using the non-linear load flow function for the constraints.

Table 5.9 Simulation results for the multiple congestion between bus bars ‘1’ and ‘2’, ‘1’ and ‘3’, ‘11’ and ‘19’ taking into account non-linear load flow function

Simulation results	***Optimization methods***			
	GA	*MVMO*	*PSO*	*ACO*
Simulation time in s	1317.26	1687.47	1372.44	1098.12
Power plants (start-up)	3, 16 and	3, 16 and	3, 16 and	3, 16 and
Power plants (drive down)	19	19	19	19
Active power changes in MW for start-up	176.59, 291.74 and 118.86	176.59, 291.74 and 118.86	176.59, 291.74 and 118.86	176.59, 291.74 and 118.86
Active power changes in MW for driving down	587.19	587.19	587.19	587.19
Total costs in €/h	46414.90	46414.90	46414.90	46414.90

In this scenario, the metaheuristic methods have a large computation time as well. The optimal solution is using the same power plants as in the previous case. However, the needed power generation changes, resp. the total costs, are less than before. Hence, there is a deviation of 3.73% or 1733.99€/h from the optimal total costs of 46414.90€/h.

5.3 Redispatch optimization considering the power plant cycling costs

Furthermore, the developed optimization techniques are adapted for the non-linear redispatch optimization problem to consider the PPCC. They are tested in the previously described small network model and simplified network model of the ENTSO-E power grid as well as in chapter 5.2. To verify the optimization algorithms different line congestions are simulated in the considered network models. Moreover, many scenarios with a variety of the power plant generation and start-up cost combinations are analyzed for different congested lines.

5.3.1 Simulation results in the small network model

The developed optimization techniques for solving the redispatch optimization problem considering the PPCC are tested in the simple small network model.

Due to the significant low costs, which need to be spent for the power plant start-up, in comparison with the costs for the power plant generation changes, the start-up costs can only have a sufficient influence on the total costs in some rare cases. For example, if the generation changes to remedy a congestion are low or the power plants have similar impact on the line power flow due to similar generation prices etc. Only in these cases, the start-up costs might make a rather large part of the total costs spending for the redispatch realization.

Furthermore, in the introduced redispatch optimization problem the costs for the power plant generation changes are considered in euros per megawatt hour. Hence, these calculated total costs are spent only for an hour of the redispatching. However, most of congestions take many hours. At the same time, the start-up of power plants is realized only once during a redispatch, i.e. the start-up costs must be spent only once for each power plant.

Therefore, a special test case is considered to verify the developed optimization algorithms with the binary variables for taking into account the PPCC. The initial conditions of the test grid model are taken from chapter 5.2.1.1. There is the single congestion of 30 MW on line ‘L5’. Furthermore, another cost scenario, which is based on the data from Table 3.1, is created for testing. The merit order remains the same power plants as well as in the test case from chapter 5.2.1.1. All chosen LCOE refer to the coal-fired power plant type. This power plant type is selected because the total PPCC, resp. the start-up costs, are highest for the coal-fired power plants (see Table 3.2 and Table 3.3). In addition, it is assumed that the considered line congestion is remedied for one hour.

Furthermore, the *power plant shut-down costs* are neglected for the simulations because they are very small compare to another cost types (see Table 3.4).

The costs for the realization of the start-up and active power changes are introduced in Table 5.10.

Table 5.10 Special cost scenario of the LCOE and PPCC

Power plant bus bars	***N1***	***N2***	***N3***	***N4***	***N5***	***N6***	***N7***	***N8***
LCOE in €/MWh	50	60	50	70	90	85	100	50
PPCC in €	-	-	-	-	45	250	70	-

Firstly, the redispatch optimization problem includes the sensitivity analysis, rated active powers of all power plants, their positive and negative redispatch potentials and PPCC. Here, the binary variables of the PPCC makes the optimization problem non-linear.

Therefore, the simplex is incapable of solving it. However, the metaheuristic methodologies can be utilized for this task.

Table 5.11 represents the simulation results of the optimization methods for the already mentioned single congestion on line ‘L5’ considering the sensitivity analysis and PPCC.

Table 5.11 Simulation results for the single congestion of 30 MW on line ‘L5’ taking into account the sensitivity analysis and PPCC

Simulation results	***Optimization methods***			
	GA	*MVMO*	*PSO*	*ACO*
Simulation time in s	11.36	15.82	10.30	9.11
Congestion power deviation on line ‘L5’ in MW	0.9	0.9	0.9	0.9
Power plants (start-up)	5	5	5	5
Power plants (drive down)	4	4	4	4
Active power changes in MW	60	60	60	60
Total costs in €/h	1245	1245	1245	1245

The optimization methods taking into account the PPCC provide identical results. The ACO has the shortest simulation time and the MVMO – the longest one.

If the PPCC were not considered in this scenario, the optimal solution for the linear redispatch optimization problem were the selection of the power plants at bus bars ‘N4’ and ‘N6’. Furthermore, the total costs for the redispatch realization were 1051.40 €/h.

However, if the PPCC are considered, the optimal solution is the selection of the power plants at bus bars ‘N4’ and ‘N5’. Here, the total costs for the redispatching are 1245 €/h. If the optimal solution were still the selection of the power plants at bus bars ‘N4’ and ‘N6’, the total costs for the redispatch realization were 1301.40 €/h. Therefore, there is a deviation of 4.53% or 56.40€/h from the optimal total costs.

In the next step, the non-linear power flow equations are included into the redispatch optimization problem instead of the network sensitivity analysis.

Table 5.12 represents the simulation results of the developed metaheuristic optimization methods for the single congestion on line ‘L5’ taking into account the non-linear power flow function and PPCC.

Table 5.12 Simulation results for the single congestion of 30 MW on line 'L5' taking into account the non-linear power flow equations and PPCC

Simulation results	***Optimization methods***			
	GA	*MVMO*	*PSO*	*ACO*
Simulation time in s	609.94	773.71	634.12	534.08
Power plants (start-up)	5	5	5	5
Power plants (drive down)	4	4	4	4
Active power changes in MW	58.15	58.15	58.15	58.15
Total costs in €/h	1208.06	1208.06	1208.06	1208.06

In this simple test case, all introduced optimization algorithms provide identical results and have a large computation time. Here, the computation time of the ACO is the shortest one in comparison to other considered metaheuristic methods.

If the PPCC were not considered, the optimal solution were the selection of the power plants at bus bars 'N4' and 'N6' as well as in the previous case. Moreover, the total costs for the redispatch realization were only 969.18 €/h.

However, if the PPCC are considered in the optimization problem, the optimal solution for the redispatch realization is the selection of the power plants at bus bars 'N4' and 'N5'. In addition, the total costs are 1208.06€/h. If the optimal solution were still the selection of the power plants at bus bars 'N4' and 'N6', the total costs for the redispatch realization were 1219.18 €/h. Therefore, there is a deviation of 0.92% or 11.12€/h from the optimal solution.

Moreover, the needed power generation changes to remedy the congestion, resp. the total costs, are less than in the case with the consideration of the sensitivity analysis. Therefore, there is a deviation of 3.06% or 36.94€/h from the optimal total costs of 1208.06 €/h.

5.3.2 Simulation results in the simplified ENTSO-E network model

The optimization methods for solving the non-linear redispatch optimization problem considering the PPCC are tested in the simplified network model of the ENTSO-E area as well.

As already mentioned above, the start-up costs are significantly low than the costs for the power plant generation changes. Therefore, in most cases they have no influence on the total costs for the redispatch realization and can be neglected. Nevertheless, there are some rare cases when they can play a major role.

In this work, such seldom case is considered to verify the developed optimization algorithms. The initial conditions of the test grid model are taken from chapter 5.2.2. Furthermore, there is the single congestion only of 20 MW on the double power line between bus bars ‘1’ and ‘2’. The sensitivity coefficients of this congested power line are given in Table 7.1. In addition, the cost scenario from chapter 5.2.2 is utilized here as well. However, the LCOE of the power plant at bus bar ‘8’ are changed to 110 €/MWh.

The chosen LCOE refer to the coal-fired power plant type because its start-up costs are highest compared to other power plant types (Table 3.2 and Table 3.3). Moreover, it is assumed that the considered line congestion is remedied for one hour.

In addition, the PPSDC are neglected for the simulations as well as in chapter 5.3.1.

The costs for the realization of the power plant start-up are introduced in Table 5.13.

Table 5.13 Start-up costs for the scenario in the simplified ENTSO-E network model

Power plant bus bar	***1***	***2***	***3***	***4***	***5***	***6***	***7***
PPCC in €	-	-	50	-	-	95	-
Power plant bus bar	***8***	***9***	***10***	***11***	***12***	***13***	***14***
Costs in €/MWh	250	0	80	0	0	0	0
Power plant bus bar	***15***	***16***	***17***	***18***	***19***	***20***	***21***
Costs in €/MWh	0	75	0	0	105	0	0

In this case, the redispatch optimization problem includes the non-linear power flow function, rated active powers of all power plants, their positive and negative redispatch potentials and PPCC.

Table 5.14 represents the simulation results of the metaheuristic optimization methods for the single congestion of 20 MW on the double power line between the bus bars ‘1’ and ‘2’ taking into account the non-linear optimization problem.

Table 5.14 Simulation results for the single congestion of 20 MW on the power line between the bus bars '1' and '2' taking into account the non-linear power flow equations and PPCC

Simulation results	***Optimization methods***			
	GA	*MVMO*	*PSO*	*ACO*
Simulation time in s	2120.85	2715.46	1962.6	1443.61
Power plants (start-up)	3	3	3	3
Power plants (drive down)	1	1	1	1
Active power changes in MW	132.04	132.04	132.04	132.04
Total costs in €/h	710.22	710.22	710.22	710.22

The metaheuristic optimization algorithms provide identical results and have a large computation time. Here, the computation time of the ACO is shortest one in comparison to other considered metaheuristic methods. Moreover, the MVMO is the slowest algorithm from the introduced methods.

If the PPCC were not considered in this scenario, the optimal solution were the selection of the power plants at bus bars '1' and '8'. Moreover, the total costs for the redispatch realization were 505.06 €/h.

However, if the PPCC are considered, the optimal solution is the selection of the power plants at bus bars '1' and '3'. Here, the total costs for the redispatch are 710.22 €/h. If the optimal solution were still the selection of the power plants at bus bars '1' and '8', the total costs were 755.06 €/h. Therefore, there is a deviation of 6.31% or 44.84€/h from the optimal total costs.

In addition, the optimal solution for the non-linear redispatch optimization problem is exactly the same as for the optimization problem with the network sensitivity analysis due to the linearization of the power flow equations for the double power line between the bus bars '1' and '2' in the simplified network model of the ENTSO-E area has no deviation at the utilized working point.

5.3.3 Conclusions

Obviously, the simplex algorithm is the fastest introduced optimization method and provides very accurate results. Nevertheless, it cannot solve the redispatch optimization problem with the non-linear power flow equations. However, in the case of the redispatch optimization problem a linearization of the load flow function can lead to large deviations in the calculation of the line congestion amounts, especially in the highly loaded electric networks.

In most cases, the previously introduced metaheuristic algorithms provide the same results as well as the simplex method if the optimization problem is linear. However, the metaheuristic optimization methodologies need significantly more computation time. Moreover, sometimes they are not able to find the global optimum of the optimization function. In addition, these methods should be adopted and parameterized for the considered optimization problem, which is not a trivial issue and can take a lot of time. Nevertheless, the utilization of the non-linear power flow equations increases the accuracy of the redispatch optimization problem definition and, consequently, improves the optimal solutions in comparison to the standard simplex. However, the sequential simplex, which is also very fast, can be utilized to remedy congestion calculation deviations. Therefore, it delivers the same results as the stochastic optimization methods taking into account the load flow function.

Furthermore, the consideration of the PPCC can also improve the optimal solutions. But the PPCC can only have a sufficient influence on the total costs in some rare cases. For example, if the generation changes to remedy a congestion are low, or the power plants have similar impact on the line power flow due to similar generation prices. But low line congestions are usually not relevant in the transmission power grids. Therefore, the PPCC can be neglected in the redispatch optimization if it is done only for one time step. However, if the redispatching is considered in the time series, the PPCC and PPSDC can have significantly more influence on the total costs because the power plants might be started-up and shut down many times, which strongly increases the total costs.

Finally, the long computation time of the stochastic optimization methods for the non-linear redispatch optimization problem makes it difficult to use them in the online network operation. Therefore, they are more suitable for an academic research.

6 Summary and Outlook

Today, the frequency of the redispatch utilization to remedy line congestions in the power grids, especially in central Europe, has extremely raised because of the high increase of the European electricity market. Unfortunately, this process causes high costs for the transmission network operators, resp. for the end customers. Therefore, an efficient redispatch optimization has become a very important issue for the TSOs.

In this work, different optimization methodologies, which are used for the redispatch optimization including the technical and economic aspects, are introduced, implemented, compared and verified in a simple small network model and simplified network model of the ENTSO-E power grid.

Obviously, the *simplex algorithm* is the fastest optimization method and used here to solve the linear redispatch optimization problem with a linearization of the power flow function, resp. the network sensitivity analysis, and without taking into account the power plant cycling costs (PPCC). However, this linearization can lead to strong deviations in the line congestion calculations, especially in the highly loaded electric networks. Consequently, this might significantly reduce the accuracy of the optimal solutions. Here, the *sequential simplex* can be used to remedy the deviations of the standard simplex. But both simplex algorithms are not able to consider the PPCC.

Therefore, the introduced metaheuristic optimization methodologies (the *genetic algorithm*, *Mean Variance Mapping Optimization*, *Particle Swarm Optimization* and *Ant Colony Optimization*) are utilized to solve the redispatch optimization problem with the non-linear load flow equations and PPCC. Based on the simulation results, they all provide accurate solutions for the redispatch optimization with the linear and non-linear constraints (see chapters 5.2 and 5.3). However, the metaheuristic approaches have a big disadvantage, resp. a long computation time, especially in case of the consideration of the non-linear power flow function. Furthermore, sometimes they are not able to find the global optimum of the optimization problem. Moreover, the mentioned stochastic optimization methods should be adopted and parameterized for the considered optimization problem, which is not a trivial task and can take a long time. Therefore, they are not really appropriate to use them in the online network operation. Nevertheless, they are well suitable for an offline study and academic research.

In addition, consideration of the PPCC can also improve the accuracy of the optimal solutions. However, in case of single time step consideration the start-up costs can have a relevant influence on the total costs only if the generation changes to remedy a congestion are low or the power plants have similar impact on the line power flow due to similar generation prices. Furthermore, low line congestions are usually not relevant in the transmission electric networks. Hence, the PPCC can be neglected in the redispatch optimization if it is done only for a snapshot of the power grid state. However, if the redispatch is considered in the time series, the PPCC and PPSDC could have significantly more influence on the total costs because power plants may be started-up and shut down many times.

Finally, different approaches (the *Power Flow Decomposition* and two *AC Power Transfer Distribution Factors* methods) for the calculation of the sensitivity analysis are introduced, implemented, compared and verified in several standard IEEE test power grid models and the already mentioned simplified network model of the ENTSO-E area. Based on the simulation results, the PFD methodology provides the most accurate approximations of the non-linear power flow equations in all test cases. Moreover, its maximum deviation is around 9% in case of an extremely high load in the simplified ENTSO-E grid model. In case of normal load in this network model, there is no deviation from the load flow function at the utilized working point at all (see the results from chapter 5.3). Therefore, the PFD method is chosen for the calculation of the network sensitivity analysis in the test networks models.

In future works, the economic aspects of the redispatch realization could be considered in the time series. In this case, the PPCC and PPSDC may be larger share of the total costs because the power plants could be started-up and shut down many times during the redispatching. Furthermore, different RES might be included in this process as well.

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A Title Annex A

Table 7.1 Sensitivity coefficients of power lines between bus bars ‘1’ and ‘3’, ‘11’ and ‘19’

Power plant bus bar	***1***	***2***	***3***	***4***	***5***	***6***	***7***
Sensitivity coefficients of line between bus bars ‘1’ and ‘2’	0.198	-0.046	0.047	0.106	0.081	0.071	-0.005
Sensitivity coefficients of line between bus bars ‘1’ and ‘3’	0.212	0.057	-0.025	0.104	0.071	0.055	0.034
Sensitivity coefficients of line between bus bars ‘11’ and ‘19’	0.084	0.072	0.09	0.142	0.172	0.164	0.053
Power plant bus bar	***8***	***9***	***10***	***11***	***12***	***13***	***14***
Sensitivity coefficients of line between bus bars ‘1’ and ‘2’	0	-0.003	0.07	0.035	0.05	0.01	0.011
Sensitivity coefficients of line between bus bars ‘1’ and ‘3’	0.034	0.036	0.06	0.038	0.047	0.028	0.03
Sensitivity coefficients of line between bus bars ‘11’ and ‘19’	0.04	0.044	0.178	0.236	0.208	0.044	-0.009
Power plant bus bar	***15***	***16***	***17***	***18***	***19***	***20***	***21***
Sensitivity coefficients of line between bus bars ‘1’ and ‘2’	0.005	0.011	0.018	0.018	0.03	0.025	0.027
Sensitivity coefficients of line between bus bars ‘1’ and ‘3’	0.034	0.034	0.038	0.038	0.035	0.04	0.038
Sensitivity coefficients of line between bus bars ‘11’ and ‘19’	0.021	0.003	0.003	0.003	-0.218	-0.007	-0.024

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