



# Optimization Techniques for Sustainable Energy System Design

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# Contents

<b>I</b>	<b>Introduction</b>	<b>1</b>
<b>1</b>	<b>Introduction</b>	<b>3</b>
1.1	The Role of Energy Systems Amid the Energy Transition . . . . .	3
1.2	Energy Transportation . . . . .	4
1.3	Energy End-use . . . . .	5
1.4	Contribution of this Thesis . . . . .	6
<b>2</b>	<b>Background</b>	<b>7</b>
2.1	Methodological Background . . . . .	7
2.1.1	Evolutionary Algorithms . . . . .	7
2.1.2	Multi-Objective Optimization . . . . .	11
2.1.3	Multi-Objective Evolutionary Algorithms . . . . .	13
2.2	Problem Background . . . . .	19
2.2.1	Problem Domain of Energy Network Expansion Planning . .	19
2.2.2	Optimization of Energy Networks . . . . .	21
2.2.3	Problem Domain of Energy-Aware Production Planning . .	24
2.2.4	Optimization in Energy-Aware Scheduling . . . . .	25
<b>3</b>	<b>Research Framework &amp; Contribution</b>	<b>31</b>
<b>II</b>	<b>Research Papers</b>	<b>37</b>
<b>4</b>	<b>Research Papers</b>	<b>39</b>
<b>5</b>	<b>Distribution Network Optimization: Predicting Computation Times to Design Scenario Analysis for Network Operators</b>	<b>41</b>
<b>6</b>	<b>A Memetic Non-dominated Sorting Genetic Algorithm II (NSGA-II) for the Multi-Objective Flexible Job Shop Scheduling Problem with Real-time Energy Tariffs</b>	<b>43</b>
<b>7</b>	<b>A Memetic NSGA-III for Flexible Production with Real-Time Energy Costs &amp; Emissions</b>	<b>45</b>

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<b>8</b>	<b>A Two-Level Approach for Multi-Objective Flexible Job Shop Scheduling and Energy Procurement</b>	<b>47</b>
<b>9</b>	<b>Comparative Analysis of Evolutionary Algorithms for Energy-Aware Production Scheduling</b>	<b>49</b>
<b>III Conclusion</b>		<b>51</b>
<b>10</b>	<b>Conclusion</b>	<b>53</b>
10.1	Revisiting the Research Questions . . . . .	53
10.2	Implications for Research and Practice . . . . .	56
10.2.1	Implications for Research . . . . .	58
10.2.2	Implications for Network Planners and Manufacturers . . . . .	59
10.2.3	Implications for Regulators . . . . .	60
10.2.4	Implications for Society . . . . .	61
10.3	Limitations & Avenues for Future Research . . . . .	61
<b>IV Bibliography</b>		<b>65</b>

## List of Abbreviations

<b><math>\theta</math>-DEA</b>	$\theta$ -dominance Relation-Based Evolutionary Algorithm
<b>DNEP</b>	Distribution Network Expansion Planning
<b>DNO</b>	Distribution Network Optimization
<b>DR</b>	Demand Response
<b>DSM</b>	Demand-Side Management
<b>EA</b>	Evolutionary Algorithm
<b>ESS</b>	Energy Storage System
<b>FJSP</b>	Flow Shop Problem
<b>FJSP</b>	Flexible Job Shop Scheduling Problem
<b>GD<sup>+</sup></b>	Modified Generational Distance
<b>HypE</b>	Hypervolume Estimation Algorithm for Multiobjective Optimization
<b>IGD<sup>+</sup></b>	Modified Inverted Generational Distance
<b>JSP</b>	Job Shop Scheduling Problem
<b>MA</b>	Memetic Algorithm
<b>MCF</b>	Minimum Cost Flow Problem
<b>MHypE</b>	Memetic Hypervolume Estimation Algorithm for Multiobjective Optimization
<b>MMCF</b>	Multicommodity Minimum Cost Flow Problem
<b>MNSGA-III</b>	Memetic Non-dominated Sorting Genetic Algorithm III
<b>MOEA</b>	Multi-Objective Evolutionary Algorithm
<b>MOO</b>	Multi-Objective Optimization
<b>NSGA-II</b>	Non-dominated Sorting Genetic Algorithm II
<b>NSGA-III</b>	Non-dominated Sorting Genetic Algorithm III
<b>RES</b>	Renewable Energy Source
<b>RTP</b>	Real-Time Pricing
<b>TOU</b>	Time-of-Use



# Part I

## Introduction



# 1 Introduction

This thesis focuses on optimization techniques for sustainable energy system design and is structured into three main parts. Part I begins with Chapter 1, offering a motivating overview of the challenges faced by energy systems during the energy transition and mapping the current research directions in energy system design. Chapter 2 details the methodology employed in this thesis, introduces the problem domain, including scheduling and network design problems, and derives research questions. Chapter 3 outlines the research framework and highlights the contributions of this work. Part II compiles the individual papers of this cumulative dissertation. Part III provides a synthesis of the research findings. Chapter 10 integrates the contributions and discusses their implications for both academic research and practical applications, addresses the limitations of the studies, and concludes the thesis with an outlook, identifying potential areas for future research.

## 1.1 The Role of Energy Systems Amid the Energy Transition

Climate change is one of the most significant challenges of the 21<sup>st</sup> century. It is fueled by an increase in the global average temperature due to greenhouse gas emissions, mainly emitted from natural systems and anthropogenic activities (Xi-Liu & Qing-Xian, 2018). Natural systems include forest fires, earthquakes, oceans, permafrost, wetlands, mud volcanoes, and volcanoes (Xi-Liu & Qing-Xian, 2018), while anthropogenic activities as the primary driver of climate change comprise human-made emissions, for example, from energy production, industrial activities, or land use (Fawzy et al., 2020; Perone, 2024). According to McLennan et al., 2024, the consequences of climate change could encompass socio-environmental crises, including loss of biodiversity and ecosystem collapse, extreme weather events, spread of infectious diseases and economic downturns.

To counteract climate change, many countries have established targets to reduce carbon emissions. For example, the European Green Deal aims to reduce net greenhouse gas emissions by at least 55% by 2030 and ultimately have zero net emissions by 2050 (European Commission, 2019). As the source of 75% of all greenhouse gas emissions in the EU, the energy sector is a key focus of the European Green Deal and the energy transition it aims to achieve. The energy transition involves structural transformation of energy production and consumption from fossil fuels to renewable energy sources and is supported by energy investments of €396 billion per year until 2030, increasing to up to €575 billion per year until 2050.

This corresponds to the allocation of 30% of the total EU budget, highlighting the importance of the energy transition. (Widuto, 2023)

The structural changes driven by the energy transition impact entire energy systems. Edenhofer et al. (2014) define an energy system as a system that comprises all components related to generation, conversion, transport, and end-use of energy. Energy systems can be categorized into different sectors by energy carrier (e.g., electricity, heat, hydrogen, and natural gas) or consumption type (e.g., transportation, residential, industrial, or commercial / trade / services) (Ramsebner et al., 2021; Robinius et al., 2017; Schaber et al., 2013). Among these carriers, electricity plays a pivotal role in global decarbonization: It is pure exergy – defined as “the maximum possible work that can be extracted along a reversible process bound to its environment” (Bayrak et al., 2017). For example, renewable energy sources (RES) like wind and solar generate electrical energy. Moreover, electricity can be efficiently converted into nearly all other energy forms with minimal losses, making electrical energy systems vital for a cost-effective, reliable, and sustainable energy supply (Schwab, 2015, p. 3). This involves refueling electric vehicles, electricity-based heat generation (power-to-heat), or conversion of electricity into synthetic fuels (power-to-gas) (Bloess et al., 2018; Götz et al., 2016).

In order to limit the scope of this thesis, it focuses on the electricity sector and addresses challenges and opportunities in energy transport and end-use arising from the integration of renewable energies, with a particular focus on their impact on stakeholders involved. Sections 1.2 and 1.3 provide an overview of the challenges faced by energy transportation and end-use, respectively.

## 1.2 Energy Transportation

The transportation of electrical energy relies on technical infrastructure networks, including power lines and transformers. These networks, also referred to as grids, limit the capacity of energy producers and consumers to feed in or withdraw energy. Networks are categorized as distribution networks in the medium and low voltage range, and transmission networks at higher voltage levels (Sinsel et al., 2020). Distribution networks, which supply end customers and absorb surplus energy, were not originally designed to handle the fluctuating loads caused by volatile renewable energy generation. Consequently, they face technical challenges such as high power transport during regional voltage excursions and unpredictable flow patterns, alongside the need for adequate protection mechanisms (Sinsel et al., 2020). To meet future demands, expansion is necessary. Distribution network operators are responsible for both the operational and strategic planning of their networks. The high costs associated with this underscore the significance of the issue: For instance, for the German distribution network, the German Energy

Academy forecasts costs of up to 42.5 billion euros by 2030 (Höfllich et al., 2012), while the Federal Ministry for Economic Affairs and Energy estimates additional expenses of up to 48.9 billion euros by 2032 (Büchner et al., 2014).

For distribution network operators as responsible stakeholders, the expansion of their networks is a complex task. They must address network design problems to determine the optimal timing, location, and capacity for network expansions. A key challenge is the minimization of investment costs while ensuring a reliable energy supply. Increasing uncertainties, especially due to an increased feed-in into the distribution network instead of the transmission network or the transition to decentralized networks, lead to uncoordinated power flows and a higher risk of overloaded distribution networks. (Rastgou, 2024)

### 1.3 Energy End-use

The end-use of electrical energy refers to its consumption. Between 2018 and 2023, the share of renewable energies in Germany’s gross final energy consumption increased from 16.7% to 22% (German Environment Agency, 2024). As energy generation from renewable sources like wind and solar is uncertain, volatile, and difficult to control (except through curtailment), shifting flexibility to the consumption side is crucial (Warren, 2014). Therefore, demand-side management (DSM) aims to align demand with renewable generation to enhance utilization and system efficiency (Panda et al., 2023). One key concept within is price-based demand response (DR), which U.S. Department of Energy (2006) describes as “a tariff or program established to motivate changes in electric use by end-use customers in response to changes in the price of electricity over time”. While there are various types of pricing schemes, two main types are commonly distinguished: time-of-use (TOU) and real-time pricing (RTP). TOU rates are static and assign varying energy prices to different time periods, with higher prices during peak times and lower prices during off-peak periods, typically set months in advance to reflect fluctuations in electricity generation costs. RTP rates are dynamically and update at least once per day, with changes occurring hourly or even more frequent. These rates are determined either a day in advance (day-ahead pricing) or in real-time (hourly pricing). (Panda et al., 2023)

DR programs are particularly promising for industrial production, as the high energy consumption in this sector offers substantial potential for cost and emission reductions Keller et al. (2017). However, realizing these potentials requires aligning production planning with fluctuations in energy prices and emissions in the energy market and to respond dynamically to market signals in both economic and ecological terms.

## 1.4 Contribution of this Thesis

This thesis aims to contribute to the fields of energy transport and energy end-use, thereby supporting advancements in energy system design. In the area of energy transport, the focus is on infrastructure planning, specifically addressing (distribution network expansion planning (DNEP)). The research investigates how large-scale problems can be modeled linearly to simultaneously consider multiple voltage levels and recommend cost-minimal expansion plans. Complementarily, in the area of energy end-use, the focus is on energy-aware production planning, as adapting and optimizing the demand of large consumers like industrial manufacturers not only reduces the strain on the energy network but also unlocks potential savings for consumers. To this end, novel scheduling approaches in the field of energy-aware production scheduling are explored, integrating real-time energy tariffs, carbon emissions, and energy procurement decisions to minimize, among other factors, energy costs and emissions.

Both problems influence each other. The network and its capacity determine supply reliability and influence consumer costs through transport losses, while consumption patterns dictate energy demand, driving the need for expansion and shaping network planning. The combined efforts of these studies contribute to the development of comprehensive strategies for energy system optimization. By addressing both supply-side (infrastructure planning) and demand-side (energy-aware production planning) challenges, this research collectively advances methods for achieving cost-effective, sustainable, and resilient energy systems.

## 2 Background

This thesis explores optimization techniques for designing sustainable energy systems, with a focus on energy transport and end use as outlined in Chapter 1. This chapter offers an overview of the methodological background of the research and its application to the problem domain. Section 2.1 outlines the methodological background, presenting the methods applied in the conducted research. Section 2.2 builds on this by addressing the problem background, links the problem domain with operations research methods, and frames the context for the research questions investigated in this thesis.

### 2.1 Methodological Background

This thesis addresses problems for which exact methods are impractical due to their NP-hardness, making them excessively time-consuming and resource-intensive. The study employs metaheuristic algorithms, which are adapted and extended to fit the specific characteristics of the problem at hand. In particular, problems involving multiple conflicting objectives benefit from population-based approaches such as Evolutionary Algorithms (EAs), which are well-suited for exploring diverse regions of the search space, as discussed in the following sections.

Section 2.1.1 situates EAs within the broader framework of metaheuristics and introduces their structure of EAs using a classical framework as an example. Section 2.1.2 outlines the principles of multi-objective optimization (MOO). Building on this, Section 2.1.3 discusses the application of EAs for multi-objective problems and presents a detailed overview of the specific multi-objective Evolutionary Algorithms (MOEAs) employed in this thesis.

#### 2.1.1 Evolutionary Algorithms

Evolutionary Algorithms are population-based metaheuristics inspired by the principle of biological evolution. They stem from evolutionary computing, a research field within computer science inspired by natural evolution. As a metaheuristic, an EA is typically applied to solve mathematical optimization problems by searching for solutions that optimize a given objective function. (Corne & Lones, 2018)

A single-objective optimization problem is generally defined by an objective function  $f(x)$  to be minimized, as indicated in objective function 2.1. The decision variables  $x$  represent a potential solution, which must satisfy a set of inequality

constraints  $g_j(x)$  and equality constraints  $h_k(x)$ , as specified in constraints 2.2 and 2.3. (Li et al., 2024)

$$\min f_i(x), \quad i = 1, \dots, m \quad (2.1)$$

$$\text{s.t. } g_j(x) \leq 0, \quad j = 1, \dots, n \quad (2.2)$$

$$h_k(x) = 0, \quad k = 1, \dots, p \quad (2.3)$$

To solve mathematical optimization problems, EAs simulate evolution by encoding  $n$  candidate solutions as individuals of a population  $P$  and applying three distinct EA operators – selection, variation, and population update – sequentially to the population in each iteration. Algorithm 1 consolidates the general framework of a classical EA to illustrate its evolution-based approach. The encoding scheme as well as selection, variation, and population update, are detailed below. Additionally, adaptation and hybridization approaches for EAs are introduced.

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**Algorithm 1** Classical EA, based on Corne and Lones (2018)

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**Require:** Population size  $n$ , Maximum number of iterations  $g$

Generate initial population  $P_0$  of size  $n$

$t \leftarrow 0$

**while**  $t < g$  **do**

    Evaluate each candidate solution in  $P_t$

    Apply **selection** operator to get parents  $P'_t \subset P_t$  based on their rank

    Apply **variation** operator to parents  $P'_t$  to create offspring  $Q_t$

    Apply population update operator to  $P_t \cup Q_t$  to create  $P_{t+1}$

$t \leftarrow t + 1$

**end while**

**return**  $P_t$

---

**Encoding Scheme** An encoding scheme allows an EA to separate the representation of a combinatorial optimization problem from its actual variables in which it was originally formulated. In its standard form, an EA is designed to operate on vectors of decision variables and optimize them. However, Corne and Lones (2018) also explore alternative representations. For complex, constraint-based problems, decoder-based approaches can be employed. In decoder-based approaches, a *genotype* is used to create and manipulate search points, while a *phenotype* is employed for evaluating these points. A mapping process is then applied to transform the genotype into the corresponding phenotype. This mapping is also referred to as a genotype-phenotype mapping. To ensure that an optimum can be found, the mapping from genotypes to phenotypes should be bijective or surjective.

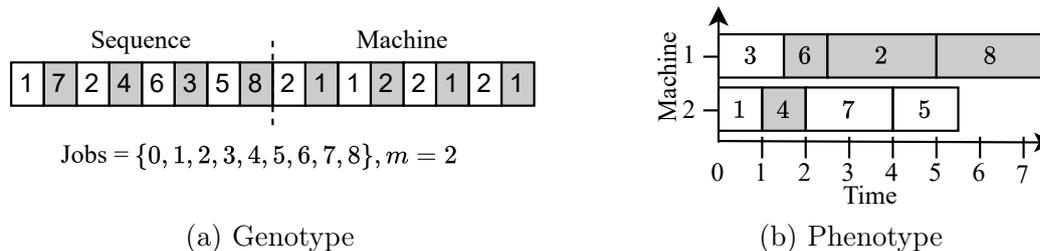


Figure 2.1: Example of a genotype-phenotype mapping

Figure 2.1 illustrates an example of a genotype-phenotype mapping, where two strings of numbers encode a solution of a scheduling problem. In Figure 2.1a, the genotype is a string divided into two sections: the first section specifies the sequence in which the jobs are scheduled, while the second section indicates the machine assignment, with two available machines to choose from ( $m = 2$ ). For improved readability, all jobs with an even identification number are highlighted in gray. Figure 2.1b illustrates the translation of the genotype into a phenotype – i.e., a machine allocation plan presented as a Gantt chart. Since the sequence gene string contains a '1' at position 0, job 0 is scheduled first. The corresponding position in the second part of the string specifies that this job is assigned to machine 2. Following this approach, all jobs are sequentially assigned to one of the two machines.

**Selection** As an evolution-inspired algorithm, the EA relies on analogies such as recombination and mutation to vary solutions within the population. Prior to that, it is necessary to select the solutions to which the recombination operators will be applied. According to Corne and Lones (2018), the combination of maintaining a population of search points and applying selection is a defining feature that sets EAs apart from most other metaheuristics.

To evaluate each solution and prioritize promising ones for the search process, an objective value – also referred to as *fitness* – determines the quality of each solution  $s$  of the population  $P$ . Effective search requires a balance between exploitation, which refines existing high-quality solutions, and exploration, which diversifies the population to cover a broader search space. Various strategies exist to adjust balance between exploitation and exploration, e.g. roulette wheel selection and tournament selection.

*Roulette wheel selection* selects each solution  $s$  with a probability proportional to its fitness value, exploiting the region of the solution space with the fittest solutions with higher probability. (Jebari, Madiafi, et al., 2013)

*Tournament selection* chooses a predefined number of solutions from a random subset of the population to prevent the solutions of the population with the highest

fitness from being selected. The chosen solutions compete in a tournament where solutions are ranked by fitness in descending order. A solution  $s$  is then selected with a probability  $\mathcal{P}(s) = p(1 - p)^{r-1}$ , where  $r$  is the ranking position of  $s$  and  $p$  is a parameter controlling the selection pressure. This increases the probability to choose solutions with less fitness and promotes exploration. (Miller, Goldberg, et al., 1995)

**Variation** Variation operators generate changes to members of the population, i.e., they carry out moves through the search space. There are various variation operators, some of which are derived from *recombination* and *mutation* processes, as explained below.

Recombination (or crossover) operator refer to combination of two or more parent solutions (identified by the selection operator) to generate new solutions. Figure 2.2 illustrates an example of a  $k$ -point crossover ( $k = 2$ ), where two children are created from two parent solutions. The children inherit values from the parents, with the parent serving as the template switching at  $k$  randomly chosen crossover points. Although the  $k$ -point crossover is straightforward to implement, it tends to produce less diverse offspring.

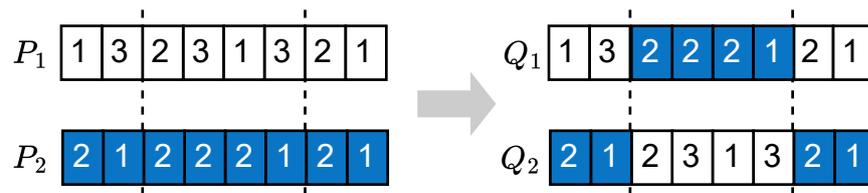


Figure 2.2: Example of a two-point crossover operation on two parent strings

The crossover strategy should be tailored to the specific problem, ensuring that the method avoids premature convergence and maintains sufficient population diversity while still fostering effective exploitation of the search process. Additionally, it is important to ensure that the offspring generated through crossover remain within the search space (and are therefore feasible). If necessary, repair operators can be introduced to achieve this. (Corne & Lones, 2018)

The mutation operator serves to maintain population diversity by introducing random variations within a subset of the population. This mechanism enables the genetic algorithm to escape local optima and access unexplored regions of the search space that may be challenging or infeasible to reach through crossover alone. Mutation thereby enhances the algorithm's space exploration. The intensity of mutation can be systematically controlled: altering a greater proportion of a solution's components increases the deviation from its original position in the search space, while mutating a larger fraction of the population shifts the algorithm's

focus from exploitation to a more pronounced exploration of the solution space. (Corne & Lones, 2018; Katoch et al., 2021)

**Adaptation and Hybridization** Two important strategies for improving EAs are adaptation and hybridization. Adaptation means tailoring algorithm components such as representation, variation operators, or selection mechanisms to the specific characteristics of the problem at hand. A well-suited adjustment of the solution method to the specific problem improves the exploration and exploitation capabilities of the search process, thereby increasing its overall efficiency. (Fister & Fister Jr, 2015)

Hybridization in the context of EAs refers to the combination of different algorithmic strategies, typically by integrating EAs with other optimization techniques—to enhance performance. While EAs are often regarded as global search algorithms because they explore a relatively broad region of the search space and are effective at escaping local optima, local search methods excel at efficiently refining solutions by exploring their surrounding neighborhood. Therefore, in addition to the previously discussed operators, EAs can be further enhanced through hybridization by incorporating additional operators. (Corne & Lones, 2018)

Corne and Lones (2018) provide the prominent example of Memetic Algorithms (MAs), which are typically EAs augmented with a local refinement component, e.g., Local Search, Tabu Search, or Simulated Annealing. A key feature that distinguishes MAs is their ability to integrate problem-specific knowledge. The No-Free-Lunch theorem (Wolpert & Macready, 1997), which provides a strong theoretical basis, emphasizes that a search algorithm’s performance is inherently dependent on the amount and quality of the problem knowledge it utilizes. Consequently, integrating such insights proves particularly beneficial for improving algorithm performance in specific problem domains.

### 2.1.2 Multi-Objective Optimization

This section introduces key concepts of MOO based on the work of Li et al. (2024) and Lobato and Steffen Jr (2017). Many real-world optimization problems involve conflicting objectives, where improving one objective often worsens another, preventing a single solution from being optimal across all dimensions of the solution space. An MOO is defined as a problem  $f : \mathcal{R}^n \rightarrow \mathcal{R}^m$  with  $m$  objectives  $f_i(x) : \mathcal{R}^n \rightarrow \mathcal{R}$ , where  $x \in \mathcal{X} \subseteq \mathbb{R}^n$  is the decision variable vector and  $\mathcal{X}$  is the feasible solution space, see objective function 2.4 and constraint 2.5 (Scholz, 2018).

$$\min f(x) = (f_1(x), \dots, f_m(x)) \quad (2.4)$$

$$\text{s.t. } x \in \mathcal{X} \subseteq \mathbb{R}^n \quad (2.5)$$

Li et al. (2024) list three characteristics for MOO problems: (1) the existence of multiple conflicting objectives, (2) the absence of a single optimal solution, and (3) the presence of a set of Pareto optimal solutions. The principle of Pareto dominance can be used to evaluate solutions comparatively. A feasible solution vector  $u \in \mathcal{X}$  *weakly dominates* another feasible solution vector  $v \in \mathcal{X}$ , denoted as  $u \preceq v$ , iff  $f_i(u) \leq f_i(v) \forall i \in \{1, \dots, m\}$ . Vector  $u$  *dominates* another solution vector  $v$ , denoted as  $u \prec v$ , when  $u \preceq v$  and  $\exists j \in \{1, \dots, m\}$  such that  $f_j(u) < f_j(v)$ . A *Pareto optimal solution* is a feasible solution that is not dominated by any other feasible solution. The *Pareto set* is the set of all Pareto optimal solutions, while the *Pareto front* is the image of the Pareto set in the objective space. (Li et al., 2024)

Solution methods for MOO can be categorized into two distinct classes: a priori methods and a posteriori methods. A priori methods simplify MOO problems by converting them into single-objective problems, typically by incorporating predefined preferences such as weights or target values. In contrast, a posteriori methods focus on generating multiple solutions along the Pareto front, providing the decision-maker with a diverse set of options from which to choose the most suitable solution after the optimization process. (Lobato & Steffen Jr, 2017)

A priori methods include (1) the weighted sum method (WSM), (2) goal programming, (3) the  $\epsilon$ -constraint method, and (4) hierarchical optimization: (1) The *weighted sum method* assigns weighted coefficients  $w_i$  to the different objective function values  $f_i(x), i \in \{1, \dots, m\}$  and minimizes their sum as shown in Equation 2.6.

$$\min f(x) = \sum_{i=1}^m w_i f_i(x) \quad (2.6)$$

This method is simple to implement, computationally efficient for non-convex problems, and can be used to obtain initial estimates for other optimization techniques. (2) In goal programming, the decision-maker specifies a target value before the solution is found, and the method minimizes the deviation of the target function values from the specified goals  $T_i$  as shown in Equation 2.7.

$$\min f(x) = \sum_{i=1}^m |f_i(x) - T_i| \quad (2.7)$$

The primary advantage of this approach is its computational efficiency, particularly when the target point is chosen within the feasible range. (3) The  $\epsilon$ -constraint

method involves minimizing one objective function while treating the other objective functions as constraints with the parameter  $\epsilon_j$  (see Constraint 2.8).

$$\begin{aligned} \min & f_1(x) \\ \text{s.t.} & f_j(x) \leq \epsilon_j, j \in \{2, \dots, m\} \end{aligned} \quad (2.8)$$

This approach effectively converts the MOO problem into a mono-objective one, with additional constraints derived from the  $\epsilon_j$  values. Thus, it provides the flexibility to obtain individual solutions from the Pareto set. (4) The Hierarchical Optimization Method is a lexicographic approach and ranks objectives based on their relative importance, where the order reflects the decreasing relative importance of the objectives. Each objective function is minimized separately, starting with the most important one. The optimization process proceeds iteratively, optimizing the next most important objective while ensuring that previously optimized, higher-ranked objectives are preserved through additional constraints or are allowed to deteriorate only by a specified deviation. (Lobato & Steffen Jr, 2017)

The main disadvantage of the methods described above is their reliance on a priori information from the decision-maker. The methods either require multiple executions or rely on predefined partial orders, thresholds, or objective weights to simplify the MOO problem into a single-objective one. A wrong choice of these parameters can lead to suboptimal results, as the reduction may not adequately capture the trade-offs between the objectives. (Lobato & Steffen Jr, 2017)

To overcome the main drawbacks of scalarization methods, a posteriori methods aim to identify non-dominated solutions or a representative subset of such solutions without depending on predefined parameters or assumptions. These methods typically operate with a population of candidate solutions, which serve as estimates for the optimal solutions. By employing a specific strategy to update this population, they generate multiple solutions in each generation, enhancing the diversity and coverage of the Pareto front. (Lobato & Steffen Jr, 2017)

A prominent group of a posteriori methods is formed by MOEAs, which are discussed in more detail in the following Section 2.1.3.

### 2.1.3 Multi-Objective Evolutionary Algorithms

MOEAs are well-suited for MOO problems as they can generate a set of solutions from which a decision maker can select a preferred solution a posteriori. A fundamental concept in MOEAs is the notion of a non-dominated solution. Such a solution is not dominated by any other solution in the population when considering all objectives simultaneously. The primary goal of an MOEA is to construct and maintain a population of non-dominated solutions that effectively represent the trade-offs between the competing objectives. (Corne & Lones, 2018)

To identify and retain non-dominated solutions, an *environmental strategy* addresses the question of which solutions from a generation are kept for the next generation and which ones are discarded. Figure 2.3 illustrates the variation and environmental selection of an MOEAs. Population  $P_t$  represents the solutions of a generation  $t$ , while  $Q_t$  contains offspring created through variation operations. The set  $R_t = P_t \cup Q_t$  combines parents and offspring, which has typically twice the size of the population  $P_t$  and thus, every second solution needs to be discarded. The environmental selection mechanism is responsible for ensuring that the population size remains constant. The choice of environmental selection, similar to the choice of variation operators, affects the balance between exploration and exploitation. A well-distributed population across the search space is crucial, as otherwise, the search may become overly concentrated in certain regions of the solution set while leaving other regions unexplored. (Li et al., 2024)

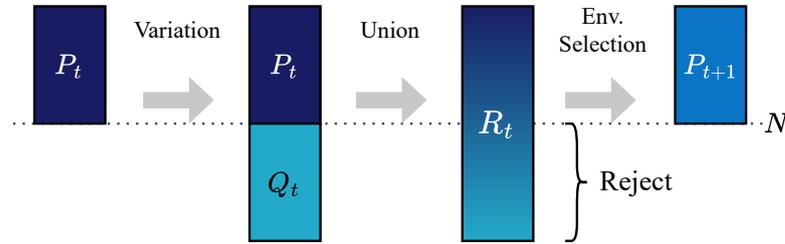


Figure 2.3: Illustration of variation and environmental selection

For environmental selection, three main paradigms for MOEAs have emerged that have a significant influence on the strategy: (1) dominance-based, (2) indicator-based, and (3) decomposition-based approaches. (1) Dominance-based MOEAs primarily use the Pareto dominance relationship between solutions and the degree of crowding to guide the selection process and maintain diversity. However, as the number of objectives increases, the number of non-dominated individuals grows exponentially, which leads to an exponential decrease in selection pressure and results in slower evolutionary progress. (2) Indicator-based MOEAs use global performance indicators to evaluate and select approximation sets. An advantage of this approach is that no additional diversity preservation mechanism needs to be incorporated. However, the computation of these performance indicators is often time-consuming, which can negatively impact the overall algorithm performance. (3) Decomposition-based MOEAs divide the MOO problem into several subproblems and select solutions based on their performance along predefined reference directions. This approach combines the advantages of scalarization methods with those of population-based approaches. However, similar to scalarization techniques, the challenge of selecting an appropriate decomposition arises in this context as well. (Li et al., 2024)

The environmental selection of the Non-dominated Sorting Genetic Algorithm II (NSGA-II), Non-dominated Sorting Genetic Algorithm III (NSGA-III),  $\theta$ -dominance Relation-Based Evolutionary Algorithm ( $\theta$ -DEA), and Hypervolume Estimation Algorithm for Multiobjective Optimization (HypE) are presented as examples, as these four EAs are examined in the papers of Part II in this thesis. As representatives of different paradigms, the algorithms primarily differ in terms of their environmental selection strategy, while the variation operators used (such as mutation and crossover) are generally interchangeable. These paradigms are particularly relevant in addressing scalability challenges that arise in many-objective optimization problems (i.e., those involving more than three objectives). As Bezerra et al. (2018) discuss, MOEAs such as NSGA-II are well-suited for problems with a limited number of objectives. However, they often face limitations in terms of scalability and computational efficiency when applied to many-objective problems. In contrast, other algorithms have been specifically designed to maintain performance as the number of objectives increases.

**NSGA-II – Crowding Distance** For NSGA-II, Deb et al. (2002) propose crowding distance sort as environmental selection. The paradigm applied is classified by Bezerra et al. (2018) as a dominance-based selection mechanism, as it combines a dominance relation with a distance-based selection mechanism.

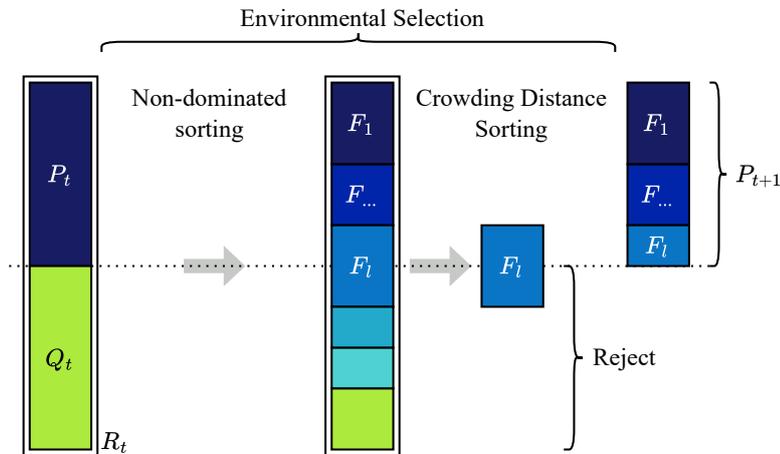


Figure 2.4: Illustration of the NSGA-II environmental selection (based on Deb et al., 2002)

In Figure 2.4, the population and its children  $R_t = P_t \cup Q_t$  are sorted into non-dominated distinct sets  $F_i$ , which are referred to as fronts. The first front  $F_1$  contains all non-dominated solutions of the population  $P_t$ , while front  $F_i$  ( $i > 1$ ) contains all non-dominated solutions of the population, excluding those that have already been assigned to preceding fronts (see Equations 2.9 and 2.10).

$$F_1 = \{x \in P_t | \forall y \in P_t : y \not\prec x\} \quad (2.9)$$

$$F_i = \left\{ x \in P_t \setminus \bigcup_{j=1}^{i-1} F_j | \forall y \in P_t \setminus \bigcup_{j=1}^{i-1} F_j : y \not\prec x \right\} \quad (2.10)$$

Since  $P_{t+1}$  must remain a fixed size  $n$  and  $|R_t| > n$ , the algorithm cannot transfer all solutions from  $R_t$  to  $P_{t+1}$ . Thus, the algorithm iterates through the fronts  $F_i$  and selects solutions for inclusion in  $P_{t+1}$  until the desired population size is reached. There exists a front  $F_l$  where not all solutions are transferred, such that  $|\bigcup_{j=1}^{l-1} F_j| \leq n$  and  $|\bigcup_{j=1}^l F_j| > n$ . Consequently, all solutions from fronts  $F_j$  with  $j > l$  are discarded, and the algorithm must decide which solutions from  $F_l$  to retain. To decide, which solutions in  $F_l$  are selected for inclusion in  $P_{t+1}$ , each solution receives a crowding distance score, calculated based on its proximity to neighboring solutions in each objective function.

$$\Delta_s = \sum_{k=1}^m \frac{f_k(i+1) - f_k(i-1)}{f_k^{\max} - f_k^{\min}} \quad (2.11)$$

As shown in Figure 2.5a, solutions  $s \in F_l$  with the extreme objective values receive an infinitely large crowding distance  $\Delta_s = \infty$ . For all other solutions  $s \in F_l$ , Equation (2.11) shows the crowding distance  $\Delta_s$  calculation as the normalized sum of distances to their nearest neighbors in each objective  $m$  as illustrated in Figure 2.5a. When selecting solutions from  $F_l$  for  $P_{t+1}$ , those with higher crowding distances are preferred to maintain both elitism and diversity. For further details, see Deb et al. (2002)

**NSGA-III – Niching & Association** In a later work, Deb and Jain (2013) criticize the computational cost of calculating crowding distance. Since compromising on diversity estimation leads to poor solution distributions, they replace crowding distance with a niching approach in NSGA-III. This also signifies a paradigm shift. The diversity mechanism employed in NSGA-III utilizes weight-based reference lines to map the distribution across the objective space, thereby categorizing it within the decomposition-based approach paradigm.

If  $|\bigcup_{j=1}^l F_j| > n$ , the algorithm performs normalization, association, and niching: First, all solutions in  $\bigcup_{j=1}^l F_j$  are normalized, denoted by  $\tilde{F} = (\tilde{f}_1, \dots, \tilde{f}_m)^T$ . Second, Figure 2.5b illustrates how reference lines (e.g., 10 reference points with three axes and 7 dashed vectors) are drawn through the normalized solution space, starting from the origin and passing 10 evenly distributed reference points. Each solution  $s$  is assigned to the reference line with the minimum perpendicular distance. Finally,

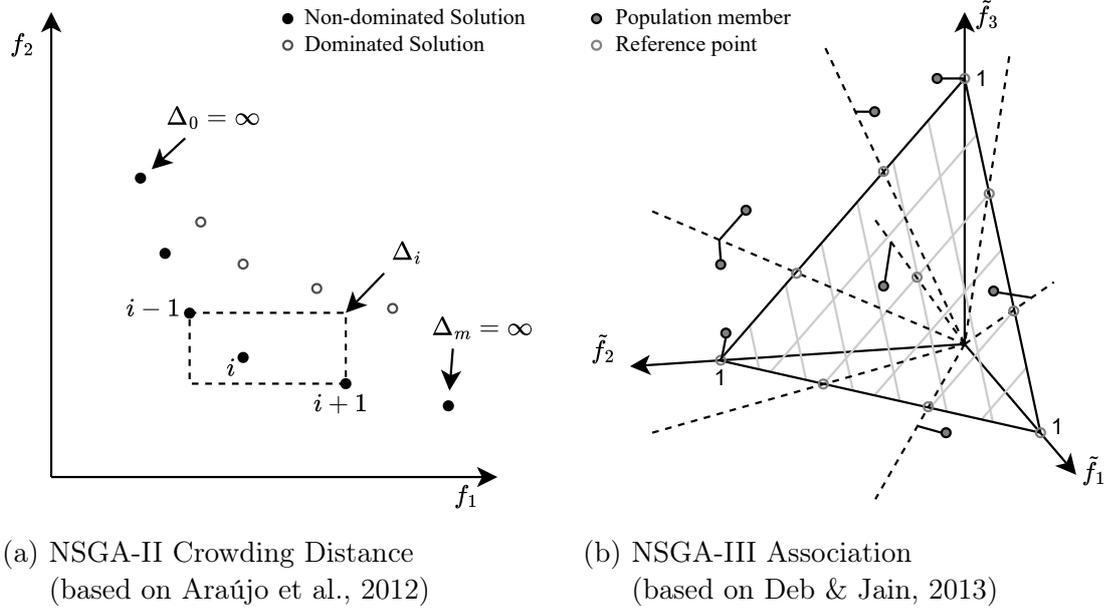


Figure 2.5: Illustration of Environmental Selection I

the niching procedure iteratively adds solutions from  $F_l$  to  $P_{t+1}$ , prioritizing those associated with the sparsest reference lines, until the desired number of individuals is reached and  $|\bigcup_{j=1}^l F_j| = n$  holds. For further details, see Deb and Jain (2013).

**$\theta$ -DEA –  $\theta$ -domination** Similar to NSGA-III,  $\theta$ -DEA normalizes the solutions and creates reference lines through the normalized objective space. However, in contrast to the NSGA-III,  $\theta$ -DEA employs an environmental selection mechanism based on a weighted  $\theta$ -dominance instead of a fitness function value. The paradigm applied here is classified by Zhang et al. (2021) as a decomposition-based dominance relation, as it combines a decomposition of the objective space into directional vectors with a dominance-based selection mechanism.

Function  $\tilde{f}(x)$  represents the normalized objective function for a solution vector of a solution  $x$ . To evaluate  $\tilde{f}(x)$ , a line  $L$  is passing through the origin in a given direction of every reference point  $\lambda_j \in \{\lambda_1, \dots, \lambda_n\}$  as shown in Figure 2.6a. Value  $u$  is the projection of  $\tilde{f}(x)$  onto  $L$ . The evaluation metric  $\mathcal{F}_j(x) = d_{j,1}(x) + \theta d_{j,2}(x)$  combines the distance  $d_{j,1}(x)$  from the origin to  $u$  and the perpendicular distance  $d_{j,2}(x)$  between  $\tilde{f}(x)$  and  $L$ , with the latter weighted by a predefined penalty parameter  $\theta$ . Cluster  $C_j, j \in \{1, \dots, n\}$  comprises all individuals with minimum  $d_{j,2}(x)$ . A classification into fronts is achieved via non-dominated sorting, employing  $\theta$ -dominance instead of Pareto dominance. A solution  $x$   $\theta$ -dominates another

solution  $y$ , iff  $x \in C_j$ ,  $y \in C_j$ , and  $\mathcal{F}_j(x) < \mathcal{F}_j(y)$ . For further details, see Yuan et al. (2015).

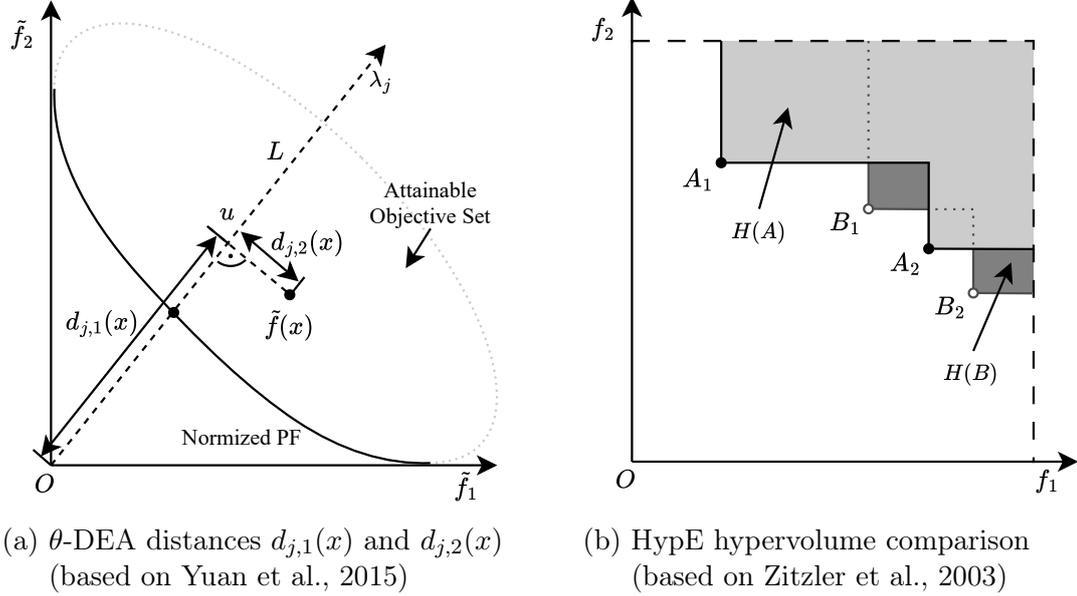


Figure 2.6: Illustration of Environmental Selection II

**HypE – Hypervolume indicator** HypE is a MOEA that follows an indicator-based paradigm as it evaluates approximation sets via the hypervolume indicator to guide the search process. The hypervolume indicator  $H(A)$  measures the volume in the objective space that is dominated by an approximation set  $A$ . While fully sensitive to Pareto dominance, it also offers the advantage of scalability with respect to the number of objectives. (Bader & Zitzler, 2011)

Figure 2.6b shows an example of a hypervolume comparison between two incomparable sets  $A$  and  $B$ , highlighted in two different shades of grey. The hypervolume comparison method is  $\not\prec$ -compatible and  $\triangleright$ -complete, meaning that if the hypervolume of  $A$  is greater than the one of  $B$ , there is no element  $b$  in  $B$  dominating an element  $a$  in  $A$  ( $H(A) > H(B) \Rightarrow A \not\prec B$ ) and if all elements in  $A$  dominate the elements of  $B$  or are equal, then the hypervolume score of  $A$  is greater than the one of  $B$  ( $A \triangleright B \Rightarrow H(A) > H(B)$ ), respectively (Zitzler et al., 2003). Please refer to Bader and Zitzler (2011) for a detailed explanation of the mathematical calculation.

The HypE assigns fitness values using the hypervolume indicator, estimated via Monte Carlo simulation to manage computational complexity. For an objective space  $Z \in \mathbb{R}^n$ , it uses a sampling set  $S := \{(z_1, \dots, z_n) \in Z \mid \forall 1 \leq i \leq n : l_i \leq z_i \leq$

$u_i\}$ . The lower bound  $l_i := \min_{a \in P} f_i(a)$  is the minimum fitness of all individuals  $a$  in the population  $P$ . The upper bound  $u_i := \max_{(r_1, \dots, r_n) \in R} r_i$  is given by a reference set  $R \subset Z$  of non-dominated objective vectors. Sampling  $M$  vectors uniformly at random from  $S$ , the hypervolume is approximated as the product of the sampling box volume  $V$  and the proportion of sampled points dominating  $R$  and dominated by  $P$ . For selection, HypE prioritizes solutions that maximize hypervolume coverage. For further details, see Bader and Zitzler (2011).

## 2.2 Problem Background

This thesis focuses on optimization techniques for designing sustainable energy systems, with a particular emphasis on distribution network expansion planning and industrial energy-aware production planning as outlined in Chapter 1. Section 2.2.1 introduces the problem domain of distribution network planning, while Section 2.2.2 addresses optimization of energy networks, explaining how optimization methods support infrastructure investment decisions. Section 2.2.3 presents the problem domain of energy-aware production planning to align consumption with grid-friendly, environmentally sustainable, and cost-effective periods, while Section 2.2.4 explores optimization in energy-aware scheduling. The subsections highlight connections between technical challenges in the energy sector and established problem classes in operations research, ultimately identifying areas requiring further research.

### 2.2.1 Problem Domain of Energy Network Expansion Planning

This section addresses the design of energy networks. To understand the complexity of planning electrical networks, it is essential to first outline their basic functionality.

Electrical networks transport energy from generation sources such as power plants through power lines or feeders to end-users, including industries and households. The electric power  $P$  transmitted in a circuit is a nonlinear function, which in a direct current network corresponds to the product of voltage  $V$  and current  $I$ . During transmission, a nonlinear power loss  $p^{loss} = I^2 \cdot R$  occurs, which is directly influenced by the line resistance  $R$  – depending on factors such as the line’s material, length, thickness – and the magnitude of the current  $I$ . (Weber et al., 2022)

While energy can be transmitted with low losses at high voltage and low current, it must be delivered at lower voltages and higher currents for consumer use. This necessitates a multi-level distribution network structure. Figure 2.7 illustrates a German Electrical grid as an example. High-voltage distribution (up to 110 kV) is connected to the transmission grid (220 - 380 kV) and transports energy over long distances and connects medium-sized power stations, energy-intensive industries and medium-voltage networks. Medium-voltage networks (6 - 30 kV) serve urban areas and large commercial consumers, while smaller power stations feed in energy.

Low-voltage networks (0.23 - 0.4 kV) deliver electricity to residential and small commercial buildings and also absorb excess energy generated by them, for example from photovoltaic systems. Transformers are used to connect these voltage levels and enable the step-down or step-up conversion of voltage as needed across the network. (Weber et al., 2022)

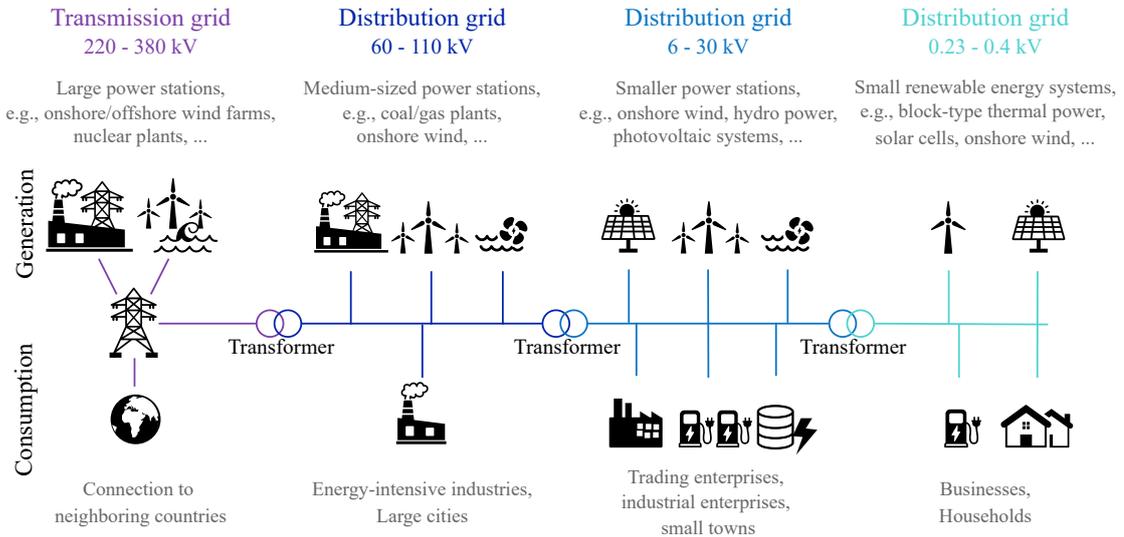


Figure 2.7: Illustration of a German Electric grid, based on BMWi (2012)<sup>1</sup>

Designing an energy network is usually based on an existing one, which is why it is also referred to as distribution network expansion planning (DNEP) or distribution network optimization (DNO). DNEP pursues the goal of an economical and reliable supply and combines aspects of both (a) network design and (b) network flow problems. (a) On the one hand, it involves determining the necessary infrastructure changes, such as installing new power lines, upgrading existing ones to higher capacities, or expanding substations to ensure consumer demand is met through a radial topology. (b) On the other hand, designing electrical distribution network requires calculating power flows to verify compliance with constraints related to voltage magnitudes at transformers and consumers, current flows in power lines, and energy losses. For example, lines cannot be drawn arbitrarily, as the losses increase depending on the resistance and current and the power could reach the consumer outside the permissible voltage. Uncertainty further complicates the problem, as varying short-term fluctuations in network demands (e.g., due to time of day or weather conditions) and long-term structural changes (e.g., new consumers and producers) are unknown. (López et al., 2018; Sabillón et al., 2018)

<sup>1</sup>The icons in Figure 2.7 are provided by the graphic design team at UXWing and available under a free license.

### 2.2.2 Optimization of Energy Networks

To model distribution networks as mathematical optimization problems, a graph serves as the fundamental structure. This thesis assumes basic knowledge of graph theory and refers to Korte et al. (2018) and Diestel (2025) for further details. Let  $G = (V, E)$  be a graph with  $s, t \in V$  two fixed vertices as source and sink nodes, respectively, and the capacity map  $u : \vec{E} \rightarrow \mathbb{N}$ , then the quadruple  $N := (G, s, t, u)$  is a network. A network can model the transport of goods by defining flows that move from the source to the sink. To model an energy network, the source represents all producers, such as power plants or RES, while the sink would aggregate the network's demands, including those from industry, commercial sectors, and households. The nodes of the network are connected to the source or sinks or correspond to switchgear cabinets, while the edges represent the power lines that connect nodes within the same voltage level. Transformers are also modeled as edges, but they link nodes across different voltage levels. In the case of an electrical power network, the transported commodity is electric power, which is determined by the product of voltage and current at a given point in the network.

For DNEP, ensuring a reliable connection of all producers and consumers and maintaining power flow is essential for a valid solution (López et al., 2018). For a standard DNEP problem, Sabillón et al. (2018) formulate the Objective Function (2.12), which minimizes the power losses across all lines connecting a node  $k$  with all its adjacent nodes  $m \in \alpha(k)$ , where  $R_{km}$  denotes the line resistance and  $I_{km}$  represents the electric current flow from  $k$  to  $m$ . Non-linear constraints account for the balances of current flow, active power, and reactive power, while also ensuring a correct voltage drop along each line. Costs for the installation and operation of distribution network elements such as power lines or transformers are neglected in this formulation. For a detailed description of the DNEP problem, this thesis refers to Sabillón et al. (2018).

$$\min \sum_{m \in \alpha(k)} R_{km} I_{km}^2 \quad (2.12)$$

To optimize investment decisions in energy network design, the field of operations research provides various subclasses of network problems. The strategic nature of planning investments for an energy network suggests that the class of (a) network design problems provides a suitable foundation for modeling a DNEP problem, while the required computation of power flow aligns the problem with the class of (b) network flow problems.

(a) Network design problems focus on identifying a subgraph that meets specified connectivity requirements. A well-known example in this category is the Steiner

tree problem, where the objective is to find a minimum-weight tree within an undirected graph with weighted edges that spans a given set of nodes. (Diestel, 2025)

(b) Network flow problems involve determining a feasible flow within a given graph that satisfies three fundamental conditions in its basic form: (1) The flow from node  $x$  to node  $y$  must equal the negative flow from node  $y$  to  $x$ . (2) Except for the source and sink, the sum of all inflows and outflows at any node must be zero. (3) The flow on each edge must not exceed its predefined capacity. A well-known network problem is the Minimum Cost Flow Problems (MCFs), which focus on transporting goods from sources through edges to sinks at minimal cost. (Diestel, 2025)

In the context of MCFs, a directed graph  $G$  with capacities  $u : E(G) \rightarrow \mathbb{R}^+$  and values  $b : V(G) \rightarrow \mathbb{R}$  is given, where positive  $b$ -values indicate supply and negative ones indicate demand, satisfying  $\sum_{v \in V(G)} b(v) = 0$ . To transport goods from supply nodes via edges to demand nodes, a function  $f : E(G) \rightarrow \mathbb{R}^+$  is defined such that  $f(e) \leq u(e)$  for all  $e \in E(G)$ . The flow's cost is determined by a cost function  $c : E(G) \rightarrow \mathbb{R}$  assigned to each edge. A  $b$ -flow in  $(G, u)$  is a flow satisfying flow conservation at each node. The objective of the MCF is to find a  $b$ -flow that minimizes the total cost, provided such a flow exists. If multiple types of flows, known as commodities, are transported simultaneously through the same network, this is referred to as a Multicommodity Minimum Cost Flow Problem (MMCF). (Korte et al., 2018)

Despite being distinct problem types, the DNEP problem introduced by López et al. (2018) and the MCF share key similarities: Both model classes aim to minimize costs, modeled as power losses in DNEP and variable flow costs in MCF. Both model classes involve flow considerations, with DNEP accounting for flow losses due to voltage drops, while MCF enforces strict flow conservation. Both model classes ensure demand fulfillment at nodes, where DNEP represents demand through a combination of different flow characteristics, and MCF models it as incoming flow of one or more commodities.

These similarities make it possible to formulate DNEP as a linear MMCF model as illustrated in Figure 2.8. However, adapting the MMCF to accurately model an electrical distribution network requires several adjustments: First, the network is represented as a multicommodity graph, with node demands  $b^A$  and  $b^V$  reflecting the required amounts of amperes and volts, respectively. Second, the graph is modeled as a multigraph to allow for parallel edges with distinct characteristics – illustrated in Figure 2.8 as three different edge types ( $\epsilon \in T = \{\alpha, \beta, \gamma\}$ ) with varying capacities  $u_\epsilon$  for the flow of the commodity amperes (A) on an edge  $\epsilon \in T$ . To account for voltage drops along the network, an estimated loss  $\Delta_\epsilon$  is assigned to each edge and the voltage demand  $b^V$  is treated with a soft constraint, allowing

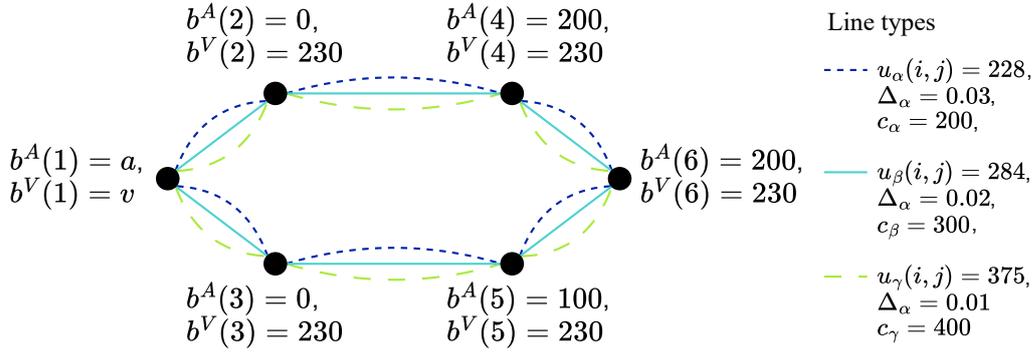


Figure 2.8: Example MMCF for Energy Distribution

slight deviations from the target voltage. This flexibility helps avoid infeasibility issues that could otherwise arise due to unavoidable voltage losses across the network. Third, as a strategic planning problem, a fixed cost  $c_\epsilon$  can be assigned to the use of an edge, representing installation costs. Thus, investment costs can be minimized through objective function (2.13), while constraints ensure correct electrical flow behavior.

$$\min \sum_{(i,j) \in E} \sum_{\epsilon \in T} x_{ij\epsilon} \quad (2.13)$$

While the linear MMCF model is less precise in representing electrical flows, it offers lower computational complexity. This reduction in complexity enables the solution of significantly larger problem instances of distribution areas within acceptable computation times. Moreover, it opens up new opportunities for scenario-based approaches: for instance, failure scenarios of network components can be incorporated to design networks that remain operational and capable of reliably supplying consumers even in the event of partial outages. Thus, the linear MMCF model not only improves scalability but also allows for the consideration of reliability aspects in distribution network planning by integrating different layers of operational uncertainty. At the same time, it raises the question of how scalable such scenario-based analyses truly are, especially when considering the diversity and complexity of possible failure constellations. To address this, this thesis investigates the computational performance of the proposed modeling approach under various given scenarios and asks:

**(RQ1)** *How do scenario characteristics affect the model's computational solution time?*

Answering this question provides practical insights for designing scenario analyses

that consider time and computational resource constraints. For decision-makers in distribution network expansion planning, this can support judgments about whether a holistic optimization of their distribution networks can be solved within reasonable time and computational resources – or whether it is more effective to decompose the network into smaller instances to enable separate, yet comprehensive, planning of large-scale distribution areas.

### 2.2.3 Problem Domain of Energy-Aware Production Planning

This section provides an overview of energy-aware production planning, placing it within the broader context of manufacturing scheduling. According to Pinedo (2022), production planning in manufacturing is a decision-driven process in which incoming orders are converted into jobs with associated due dates. These jobs must be assigned to available resources – typically machines – over a defined time horizon, with the aim of optimizing one or more performance objectives. One of the most common goals in this context is to minimize the makespan, i.e., the total time required to complete all jobs. Due to the inherent complexity of manufacturing systems and the uncertainty of real-world conditions, such as machine breakdowns or processing delays, scheduling is essential to maintain operational efficiency and control. (Pinedo, 2022)

Research in this field reflects a wide variety of priorities. They prioritize different key performance indicators, address diverse operational constraints, and employ a broad range of solution strategies. For a comprehensive overview of production scheduling approaches and their applications, the reader is referred to the survey by Geurtsen, Didden, et al. (2023), which reviews techniques for production, maintenance, and resource scheduling.

Energy-aware production planning considers energy consumption as a relevant factor of schedule optimization. In such approaches, energy becomes either a primary or secondary optimization objective. Depending on the production context, energy demand may be incorporated directly into the objective function – particularly if it can be influenced by operational choices such as machine speed adjustments or intentional idle periods. In cases where energy consumption per task is fixed, its optimization is often linked to timing decisions, especially when energy costs fluctuate over time. In this regard, DR programs, such as TOU or RTP tariffs, can dynamically influence energy costs, enabling the scheduling process to support manufacturers in adapting to demand-side management signals. Studies like Keller et al. (2017) indicate that industrial consumers can achieve substantial cost savings by adapting their energy loads more flexibly. This flexibility can be achieved by shifting energy-intensive tasks to periods with lower energy prices or higher availability of renewable energy sources, without jeopardizing economic objectives like minimizing the makespan.

### 2.2.4 Optimization in Energy-Aware Scheduling

To situate energy-aware production planning within a broader scientific context, this section adopts the perspective of operations research. According to Pinedo (2022), two key components must be considered to accurately model real-world scheduling problems: (1) The machine environment that defines the available resources and (2) the objectives to be optimized. Additionally, a third but optional key component is related to the processing characteristics of the tasks and the constraints that must be satisfied, e.g., release dates, due dates, or job priority factors.

(1) The simplest machine environment is the single-machine problem, where all tasks are processed on a single resource. More complex scenarios include parallel machine problems, where tasks can be assigned to identical machines operating simultaneously, or machines with different speeds. Two prominent scheduling problem classes are the Flow Shop and Job Shop problems. In a Flow Shop Problem (FJSP), multiple machines are arranged in series, and each job is divided into a sequence of operations. The machines can be sequentially numbered as  $1, \dots, m$ , and the operations of job  $i$  are denoted as  $(i, 1), \dots, (i, m)$ , where each operation  $i, j$  corresponds to the processing step of job  $i$  on machine  $j$ . This fixed sequence ensures that every job follows the same predetermined order through the machine sequence. In contrast, in a Job Shop Scheduling Problem (JSP) the jobs still consist of multiple operations with predefined precedence constraints, but the flow of work is not unidirectional. The order in which the jobs are processed on the machines is also fixed, although it is different for each job, and no strict starting or ending machine is required. An extension of the JSP is the Flexible Job Shop Scheduling Problem (FJSP), where each operation can be assigned to one of a set of given machines, increasing flexibility in operation allocation. (Baker & Trietsch, 2018; Pinedo, 2022)

Interested readers are referred to comprehensive reviews for further information. For example, Chaudhry and Khan (2016) explore several FJSP models and their respective solution methods, while Dautère-Pérès et al. (2024) provide a general overview of FJSPs, highlighting different criteria, constraints, configurations, and solution strategies.

(2) The objectives of scheduling problems can vary widely, depending on the context and the specific requirements of the application. As outlined by Pinedo (2022), common objectives in scheduling problems include: minimizing the makespan, minimizing the maximum lateness, which reflects the most significant deviation from due dates, or minimizing the total weighted completion time, where processing and waiting times are weighted to account for holding or inventory costs.

Bänsch et al. (2021) provide a comprehensive overview of energy-aware scheduling, emphasizing the integration of energy consumption into scheduling decisions. They

report that approximately 63% of the studies they reviewed adopt multi-objective formulations, with the trade-off between energy costs or consumption and time-based objectives being the most prominent. However, much of the existing research assumes fixed energy prices or TOU-based tariffs and does not fully address the challenges posed by highly dynamic RTP rates. Complementary to this, in their review of energy-aware scheduling in intelligent production systems, Gao et al. (2020) highlight that only a small fraction of the surveyed studies (13%) rely on exact solvers due to problem complexity, while the majority (59%) employ swarm or evolutionary algorithms. Notably, the use of memetic extensions is not addressed in their review.

Another gap arises from the fact that existing studies rarely incorporate explicit mechanisms in the encoding to account for time-dependent energy prices. To effectively solve time-indexed scheduling problems under dynamic RTP tariffs, evolutionary algorithms must be adapted to the structural characteristics of the problem. For instance, Jiang and Wang (2020) propose an encoding scheme in which one group of genes represents the operation sequence and another encodes machine assignments, while start and end times are implicitly determined in the phenotype to ensure feasibility without overlaps. Similarly, Geng et al. (2024) extend this approach by introducing a third gene group for assigning operations to factories. This encoding has the advantage of facilitating the generation of feasible solutions, provided that operations are assigned only to valid machines – an aspect particularly important when applying variation operators such as crossover. However, this representation lacks explicit control over start times within the genotype, limiting the algorithm’s ability to directly exploit dynamic energy prices. Building on the research gap concerning tailored memetic algorithms for computing RTP-based energy-aware schedules, the first research question in the domain of energy-aware scheduling focuses on the use of memetic algorithms for solving time-indexed scheduling problems with RTP tariffs and is formulated as follows:

**(RQ2)** *How can a multi-objective memetic algorithm optimize makespan and energy cost for energy-aware scheduling under the influence of dynamic real-time energy tariffs?*

Answering this question aims to evaluate the fundamental suitability of memetic evolutionary algorithms for energy-aware scheduling. Additionally, it seeks to generate practical insights that support decision-makers in incorporating rapidly fluctuating energy prices into their production planning under RTP schemes.

Beyond energy costs, the sustainability of energy production can also be considered in production planning. Rather than accounting for emissions solely through CO<sub>2</sub> taxes – thereby implicitly incorporating them into energy costs – it can be beneficial to explicitly include emissions in the planning process. This approach allows for targeted efforts to reduce a company’s carbon footprint, which can be

advantageous in meeting regulatory requirements, appealing to environmentally conscious customers, and maintaining legitimacy with external stakeholders (Maia et al., 2022).

Adding emission minimization as a third objective to an existing bi-objective optimization model, which focuses on minimizing makespan and energy costs, introduces a new dimension that may conflict with the other two objectives. This conflict arises because energy costs are driven by market dynamics, whereas emissions are environmentally driven, meaning the two factors may behave independently. Consequently, the problem becomes a tri-objective optimization task. As the structure of the solution space becomes more complex in three dimensions, differences in the distribution and scalability of solutions may emerge depending on the algorithm used (Li et al., 2024). Therefore, it is advisable to apply a different solution method than the one used for RQ2. For manufacturers aiming to integrate sustainability into production planning, the addition of a third objective presents the challenge of evaluating the trade-offs between economic efficiency and environmental impact. This leads to the following research question:

**(RQ3)** *How do scheduling decisions that prioritize one objective — makespan, energy cost, or emissions — affect the others?*

Another important aspect to consider is the uncertainty in planning. As dynamic tariffs, RTP rates are not only volatile but are also announced only one day in advance, making future prices unknown. Forecasting these prices is challenging, as they are driven by market dynamics. Similarly, emissions are influenced by the share of renewable energy in the energy network, which in turn is subject to exogenous factors such as solar radiation or wind intensity, making them highly variable. Given the difficulty of making accurate predictions, a solution method must be capable of effectively adapting to changing conditions of energy prices and emissions.

Greater flexibility in energy procurement can be achieved through behind-the-meter RES, which allow for self-generated energy consumption, and energy storage system (ESS), which can act as controllable – chargeable and dischargeable – resources for energy (Chen et al., 2022; Dong & Ye, 2022). The challenge arises in extending a multi-objective approach that simultaneously minimizes makespan, energy costs, and emissions by incorporating the uncertainties of a dynamic energy market and leveraging on-site energy from RES and ESS.

Building on this, it becomes essential to understand how such dynamic and uncertain conditions affect not only the optimization process itself but also the outcomes and their practical relevance. Although uncertainty does not change the structure of the solution space, it limits the reliability of evaluating solution quality in terms of energy costs and emissions at the time of planning, as these depend on future market prices and energy availability. Consequently, suitable solution

approaches must be capable of accounting for such uncertainties and integrating new information over time to support robust and informed decision-making. This highlights the need to adapt deterministic approaches, as their reliance on fixed input data limits their ability to cope with dynamic and uncertain conditions.

The adaptation of methods to incorporate uncertainty brings forth the fundamental question of how such uncertainty-aware approaches can be successfully applied in real-world settings and under what circumstances they provide measurable advantages. Key considerations related to the uncertainty of energy prices and availability include seasonal fluctuations in potential energy savings, the level of control over conflicting objectives, and the practical implementability of the resulting schedules. Adapting an uncertainty-aware planning approach, in combination with a broader range of potential energy sources, the central question can be subdivided into the following three research questions:

- (RQ4.1) *How do different seasonal conditions affect potential savings in energy cost and emissions?*
- (RQ4.2) *To what extent can decision-makers influence the makespan, energy cost, and emissions of schedules?*
- (RQ4.3) *How feasible are energy cost and emission-based schedules for practice?*

In addition to research questions addressing aspects of the application domain, this thesis also examines different solution methods in comparison. Surveys, such as the one by Gao et al. (2020), indicate that existing studies on energy-aware scheduling primarily differentiate themselves based on the problem characteristics they consider, exploring various objectives and constraints for which they evaluate individual algorithms. While most of the solution methods employed are EAs and MOEAs, comparative analyses across multiple algorithms remain limited.

Problems from the field of many-objective optimization – that is, involving four or more objectives – are particularly interesting for comparing different algorithms. As the number of objectives increases, Pareto-optimal solutions grow exponentially due to more trade-offs, while dominance becomes less meaningful, as many solutions are mutually non-dominated in four or more objectives (Li et al., 2024). Particularly for MOEAs, the question arises whether MOEAs from different paradigms exhibit distinct characteristics in terms of both solution quality and efficiency when applied to the given problem, highlighting the importance of comparing various approaches.

This thesis therefore also addresses the research question:

- (RQ5) *How do MOEA design patterns vary in terms of solution efficiency and quality across different scenarios?*

Answering this question provides valuable insights for both researchers and practitioners by identifying which types of MOEA design patterns are most suitable under varying problem conditions. Overall, the research questions address various challenges within the domain of energy system design and complement each other through their different focuses and shared goals.



### 3 Research Framework & Contribution

This chapter outlines the research conducted in this thesis. It links the research questions posed in Section 2.2 to studies of this thesis and organizes their subject matter within a research framework.

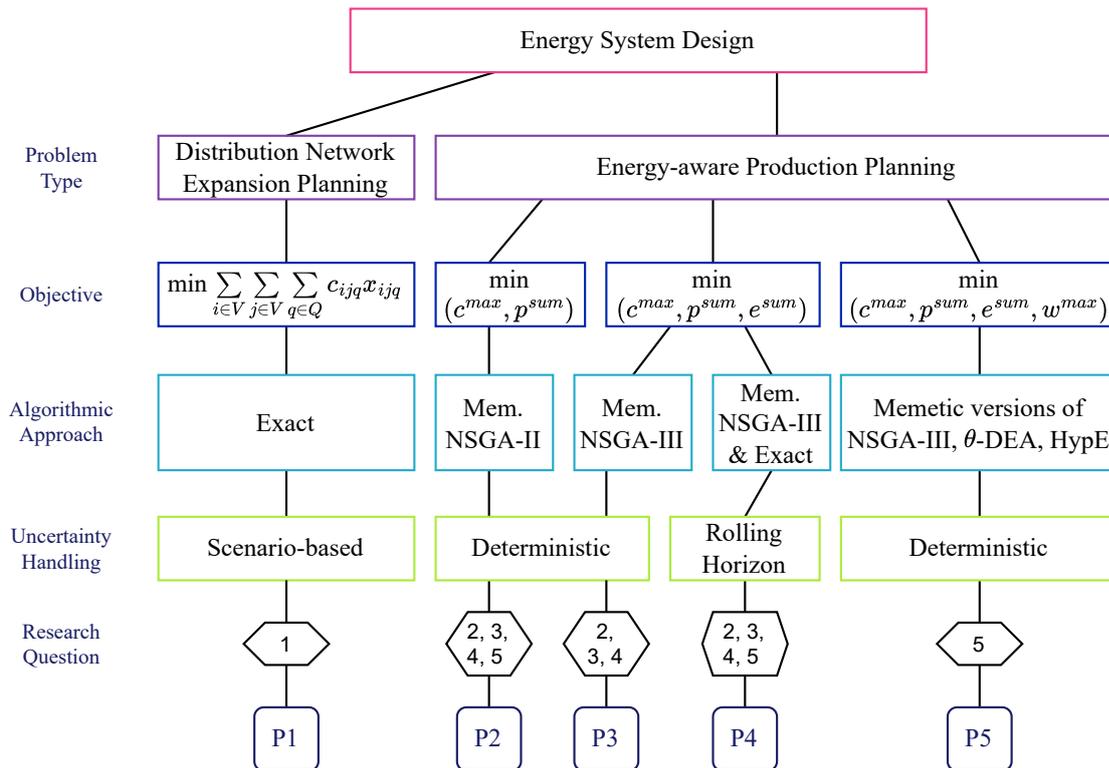


Figure 3.1: Research framework

Figure 3.1 provides a visual representation of the research framework of this thesis and outlines the focal points addressed in the respective research contributions to distinguish them from one another. All studies are concerned with problems in the field of Energy System Design. In the first level, the research studies are categorized according to the problem domain they address: distribution network expansion planning and industrial energy demand response. The second level specifies the objective function pursued within each study and, indirectly, the number of objectives considered. The third level highlights the chosen solution approach. The final level describes how uncertainty is handled in each study. The

following section provides a detailed classification of the studies along with their individual contributions.

**(P1) Distribution Network Optimization - Predicting computation times to design scenario analysis for network operators**

In the area of distribution network expansion planning, distribution network operators face the challenge of adapting their grids to evolving requirements while developing cost-effective expansion plans. This work identifies the research gap that no work exists that (1) addresses large-scale networks using exact optimization methods, (2) integrates both primary and secondary distribution networks, and (3) designs flexible topologies to ensure high reliability electricity supply for end-users. The study aims to minimize the sum over all investment costs  $c_{ijq}$  across all available network elements  $q$  and their respective usage between two nodes  $i$  and  $j$ , represented by the indicator variable  $x_{ijq}$ . It develops a linear MMCF that models the non-linear electrical flow behavior through multiple commodities and adopts an exact approach. To ensure resilience, a scenario-based approach is employed, where scenarios assume failures of network elements while maintaining the supply to the network consumers. To guide decision-makers, P1 focuses on *RQ1* and investigates how efficiently instances of this novel model can be solved.

The contributions of this work include: (1) creating a linear optimization model that incorporates the technical specifics of distribution networks, (2) conducting comprehensive computational experiments to analyze the relationships between scenario parameters and computation times, and (3) offering recommendations for infrastructure planners looking to conduct scenario analyses when planning power distribution networks.

**(P2) A Memetic NSGA-II for the Multi-Objective Flexible Job Shop Scheduling Problem with Real-time Energy Tariffs**

The second paper shifts the focus from the area of distribution network expansion planning to that of energy-aware production planning. In the area of DR, large energy consumers such as manufacturers face the challenge of aligning their production schedules with fluctuating energy prices. This work identifies the research gap that previous studies are limited to fixed or TOU rates or neglect makespan optimization when considering RTP rates. The model aims to minimize the makespan  $c^{max}$  as a traditional production scheduling objective while simultaneously minimizing the energy costs  $p^{sum}$  incurred by production. Given the multi-objective nature of the problem, its complexity, and the limited decision time required to react to dynamic prices, the paper adopts an memetic NSGA-II as its algorithmic approach.

The NSGA-II approach is selected since it has demonstrated its effectiveness across a wide range of multi-objective applications (Verma et al., 2021), including its successful use in scheduling problems (Rahimi et al., 2022). P2 focuses on the research question *RQ2* and simultaneously investigates decision-makers' trade-offs (*RQ3*, *RQ4.2*) as well as the applicability of the resulting production plans (*RQ4.3*).

The contributions of this work include: (1) developing a linear optimization model that addresses an FJSP with dynamic energy costs, (2) designing an innovative MA based on the NSGA-II, and (3) evaluating the algorithm's performance and practicality through computational experiments.

### **(P3) A Memetic NSGA-III for Flexible Production with Real-Time Energy Costs & Emissions**

In addition to fluctuating energy prices, energy-intensive industries are increasingly driven to reduce their carbon footprint. Lowering carbon emissions has become a key objective for manufacturers, as it supports their sustainability goals, helps them anticipate or respond to regulatory pressures, attracts environmentally conscious customers, and maintains their legitimacy with external stakeholders (Dahlmann et al., 2019). P3 identifies the research gap that existing studies focus on single goals, neglect the combined optimization of makespan  $c^{max}$ , energy costs  $p^{sum}$ , and emissions  $e^{sum}$ , or rely on constant or periodic TOU rates instead of accounting for the dynamics of a fluctuating energy market. To address this research gap, the third paper expands the scope of energy-aware scheduling by integrating emissions as an explicit objective and focuses on the research question *RQ3*.

The contributions of this work are threefold: (1) the formulation of an FJSP that incorporates dynamic energy costs and emissions as objectives, (2) the development of a memetic NSGA-III, and (3) the execution of computational experiments to analyze trade-offs among makespan, energy costs, and emissions. NSGA-III is applied because its reference point-based approach offers superior scalability and diversity management for problems with three objectives, making it more effective than the crowding-distance mechanism used in NSGA-II (Deb & Jain, 2013). In addition, it has delivered promising results in related FJSP contexts (Sang & Tan, 2022; Wu et al., 2021) and has already been successfully used to optimize schedules with respect to energy-related criteria (Sun et al., 2021).

### **(P4) A two-level approach for multi-objective flexible job shop scheduling and energy procurement**

The fourth paper extends the demand response problem examined in P3 and enhances the problem by integrating simultaneous energy procurement decisions from distinct sources, including the grid, behind-the-meter RES,

and an ESS. P4 identifies the research gap that no existing multi-criteria approach simultaneously minimizes makespan, energy cost, and emissions while accounting for the uncertainties of a dynamic energy market and the use of on-site energy generated by RES and ESS. The algorithmic approach, similar to P2 and P3, employs an MOEA for the generation of production schedules, while exact methods are applied to determine optimal energy procurement decisions. The study highlights uncertainties from dynamic energy prices, fluctuating emissions, and on-site energy generation. These stem from the day-ahead market structure, where prices and emissions intensities – determined by the committed energy mix – are announced daily and vary with renewable availability. To reflect this short-term planning horizon, a rolling horizon approach is used. The research questions guiding this study are *RQ4.1*, *RQ4.2* and *RQ4.3*.

The contributions of this work include three key components: (1) Formulating linear optimization models for solving the FJSP and energy procurement with multi-objective minimization of makespan, dynamic energy costs, and emissions, (2) developing a novel memetic algorithm inspired by the NSGA-III, and (3) conducting extensive computational experiments to analyze reductions in energy costs and emissions. To account for the uncertainty inherent in the problem, the solution method is implemented and evaluated using a rolling horizon approach.

#### **(P5) Comparative Analysis of Evolutionary Algorithms for Energy-Aware Production Scheduling**

The fifth paper centers on comparing solution approaches in the context of industrial energy demand response, primarily employing MOEAs. Building on previous work, the set of optimization objectives is extended by a fourth criterion – the required number of workers  $w^{max}$  – transforming the problem into a many-objective optimization problem with four conflicting goals:  $\min(c^{max}, p^{sum}, e^{sum}, w^{max})$ . This expansion significantly increases the problem's complexity, both in terms of the search space and the trade-offs between objectives. It also raises the question of whether dominance-based algorithms such as NSGA-III, which are known to struggle with increasing dimensionality, remain suitable in this context.

P5 highlights a research gap where existing studies focus on adapting individual solution approaches to specific domain challenges but often neglect comparative analyses between methodologies. The study contrasts dominance-based, indicator-based, and decomposition-based MOEA frameworks with regard to their ability to ensure convergence, diversity, and completeness of the resulting Pareto front.  $\theta$ -DEA and HypE are considered alongside NSGA-III, as they represent conceptually distinct algorithmic

approaches for solving many-objective optimization problems.  $\theta$ -DEA, as a decomposition-based method, employs a direction angle-based selection mechanism that explicitly balances convergence and diversity – a strategy that has shown strong performance in many-objective contexts (Zhang et al., 2021). HypE, selected as a representative of indicator-based algorithms, uses a steady-state search guided by direct hypervolume contribution. Its efficiency in handling many-objective problems has been confirmed in empirical studies, where it outperforms several existing MOEAs (Bader & Zitzler, 2011). Moreover, it is considered one of the most relevant indicator-based MOEAs according to Bezerra et al. (2018). By comparing NSGA-III,  $\theta$ -DEA, and HypE, this study provides a comprehensive assessment of how conceptually distinct MOEAs frameworks perform when estimating Pareto fronts, thereby addressing research question *RQ5*.

The contributions of this work include (1) formulating an energy-aware FJSP to minimize makespan, energy costs, emissions, and the number of workers, within a real-time energy market context, (2) developing memetic NSGA-III,  $\theta$ -DEA, and HypE, as representatives of different environmental selection paradigms, and (3) conducting computational experiments to evaluate the algorithms.



Part II  
Research Papers



## 4 Research Papers

This chapter presents the individual research papers that form the core of this thesis. Tables 4.1 and 4.2 provide an overview of all included publications, including their publication types, outlets, publishers, authors and full citations. All papers have been published or accepted for publication in peer-reviewed outlets.

Table 4.1: Overview of the research papers

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Distribution Network Optimization: Predicting Computation Times to Design Scenario Analysis for Network Operators	
<b>Type</b>	Journal Publication
<b>Outlet</b>	Energy Systems
<b>Publisher</b>	Springer
<b>Authors</b>	Sascha C Burmeister Guido Schryen
<b>Citation</b>	Burmeister, S. C., & Schryen, G. (2023) Distribution network optimization: Predicting computation times to design scenario analysis for network operators. <i>Energy Systems</i> , 16, 227–254. <a href="https://doi.org/10.1007/s12667-023-00572-5">https://doi.org/10.1007/s12667-023-00572-5</a>
A Memetic NSGA-II for the Multi-Objective Flexible Job Shop Scheduling Problem with Real-time Energy Tariffs	
<b>Type</b>	Journal Publication
<b>Outlet</b>	Flexible Services and Manufacturing
<b>Publisher</b>	Springer
<b>Authors</b>	Sascha C Burmeister Daniela Guericke Guido Schryen
<b>Citation</b>	Burmeister, S. C., Guericke, D., & Schryen, G. (2023) A memetic NSGA-II for the multi-objective flexible job shop scheduling problem with real-time energy tariffs. <i>Flexible Services and Manufacturing Journal</i> , 36, 1530–1570. <a href="https://doi.org/10.1007/s10696-023-09517-7">https://doi.org/10.1007/s10696-023-09517-7</a>

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Table 4.2: Overview of the research papers (continued)

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A Memetic NSGA-III for Green Flexible Production with Real-Time Energy Costs & Emissions	
<b>Type</b>	Journal Publication
<b>Outlet</b>	Croatian Operational Research Review
<b>Publisher</b>	Croatian Operational Research Society
<b>Author</b>	Sascha C Burmeister
<b>Citation</b>	Burmeister, S. C. (2025) A memetic NSGA-III for green flexible production with real-time energy costs & emissions. <i>Croatian Operational Research Review</i> , 16. <a href="https://doi.org/10.17535/crorr.2025.0009">https://doi.org/10.17535/crorr.2025.0009</a>

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A Two-Level Approach for Multi-Objective Flexible Job Shop Scheduling and Energy Procurement	
<b>Type</b>	Journal Publication
<b>Outlet</b>	Cleaner Energy
<b>Publisher</b>	Elsevier
<b>Authors</b>	Sascha C Burmeister Daniela Guericke Guido Schryen
<b>Citation</b>	Burmeister, S. C., Guericke, D., & Schryen, G. (2025) A two-level approach for multi-objective flexible job shop scheduling and energy procurement. <i>Cleaner Energy Systems</i> . <a href="https://doi.org/10.1016/j.cles.2025.100178">https://doi.org/10.1016/j.cles.2025.100178</a>

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Comparative Analysis of Evolutionary Algorithms for Energy-Aware Production Scheduling	
<b>Type</b>	Conference proceedings
<b>Outlet</b>	Large-Scale Scientific Computations
<b>Publisher</b>	Springer Cham
<b>Authors</b>	Sascha C Burmeister Till N Rogalski Guido Schryen
<b>Citation</b>	Burmeister, S. C., Rogalski, T. N., & Schryen, G. (2025) Comparative analysis of evolutionary algorithms for energy-aware production scheduling. <i>Large-Scale Scientific Computations</i>

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## 5 Distribution Network Optimization: Predicting Computation Times to Design Scenario Analysis for Network Operators

**Abstract.** The increased use of renewable energies promotes decarbonization and raises the load on power distribution networks, forcing responsible distribution network operators to re-evaluate and re-design their networks. Infrastructure planners employ a rolling-horizon planning procedure with frequent recalculations to face informational uncertainty, which requires solving multiple scenarios. Keeping complexity manageable is particularly challenging as distribution network areas may span multiple cities and counties. In this study, we focus on infrastructural decomposition, where the distribution network is decomposed into multiple parts and planning problems, which are then optimized separately. However, infrastructure planners lack the knowledge of how they should design a scenario analysis for a subnetwork to account for informational uncertainties subject to limited planning time and computing resources. Based on empirical requirements from literature and discussions with experts, we present a novel mixed integer linear optimization model that allows to use exact solution approaches for realistic large-scale distribution networks. Our approach considers the primary and secondary distribution network in an integrated way and designs a flexible topology for high reliability power distribution. We perform extensive computational experiments and a sensitivity analysis to determine correlations between the values of model parameters and computation times required to solve the resulting model instances to optimality. The results of the sensitivity analysis indicate that the combination of the number of buses, lines and the considered action scope have a considerable influence on the solving time. In contrast, a higher number of available transformers led to a better solvability of the model. From these computational insights, we derive implications for infrastructure planners who wish to perform scenario analysis for planning their power distribution networks.

Burmeister, S. C., & Schryen, G. (2023) Distribution network optimization: Predicting computation times to design scenario analysis for network operators. *Energy Systems*, 16, 227–254. <https://doi.org/10.1007/s12667-023-00572-5>



## 6 A Memetic NSGA-II for the Multi-Objective Flexible Job Shop Scheduling Problem with Real-time Energy Tariffs

**Abstract.** Rising costs for energy are increasingly becoming a vital factor for the production planning of manufacturing companies. Manufacturers face the challenge to react to dynamic energy prices and design energy cost efficient schedules in their production planning. In the literature, the energy cost-aware Flexible Job Shop Scheduling Problem addresses minimization of both makespan and energy costs. Recent studies provide multi-objective approaches to model the trade-off of minimizing makespan and energy costs. However, the literature is limited to coarse-grained time periods and does not consider dynamic tariffs where costs change at short intervals, so that production schedules may fall short on energy costs. We aim to close this research gap by considering frequently changing real-time energy tariffs. We propose a multi-objective memetic algorithm based on the Non-dominated Sorting Genetic Algorithm II (NSGA-II) with both makespan and energy cost minimization as the objectives. We evaluate our approach by conducting computational experiments using prominent FJSP-benchmark instances from the literature, which we supplement with empiric dynamic energy prices. We show results on method performance and compare the memetic NSGA-II with the results of an exact state-of-the-art solver. To investigate the trade-off between a short makespan and low energy costs, we present solutions on the approximated Pareto front and discuss our results.

Burmeister, S. C., Guericke, D., & Schryen, G. (2023) A memetic NSGA-II for the multi-objective flexible job shop scheduling problem with real-time energy tariffs. *Flexible Services and Manufacturing Journal*, 36, 1530–1570. <https://doi.org/10.1007/s10696-023-09517-7>



## 7 A Memetic NSGA-III for Flexible Production with Real-Time Energy Costs & Emissions

**Abstract.** The use of renewable energies strengthens decarbonization strategies. To integrate volatile renewable sources, energy systems require grid expansion, storage capabilities, or flexible consumption. This study focuses on industries that adapt production to real-time energy markets, offering flexible consumption to the grid. Flexible production considers not only traditional goals like minimizing production time, but also minimizing energy costs and emissions, thereby enhancing the sustainability of businesses. However, existing research focuses on single goals, neglects the combination of makespan, energy costs, and emissions, or assumes constant or periodic tariffs instead of a dynamic energy market. We present a novel memetic NSGA-III to minimize makespan, energy cost, and emissions, integrating real energy market data, and allowing manufacturers to adapt consumption to current grid conditions. Evaluating it with benchmark instances from literature and real energy market data, we explore the trade-offs between objectives, showcasing potential savings in energy costs and emissions on estimated Pareto fronts.

Burmeister, S. C. (2025) A memetic NSGA-III for green flexible production with real-time energy costs & emissions. *Croatian Operational Research Review*, 16. <https://doi.org/10.17535/corr.2025.0009>



## 8 A Two-Level Approach for Multi-Objective Flexible Job Shop Scheduling and Energy Procurement

**Abstract.** Dynamic energy tariffs in combination with energy storage systems (ESS) and renewable energy sources (RES) offer manufacturers new opportunities to optimize their energy consumption. Flexible production planning empowers decision-makers not only to minimize makespan, but also to reduce energy costs and emissions. However, flexible production planning is a major challenge due to the fact that scheduling decisions affect energy demand, whose costs and emissions depend on energy procurement decisions. In Operations Research, the Green Flexible Job Shop Scheduling Problem (FJSP) addresses production planning decisions incorporating resource, environmental, and economic objectives. The Energy Procurement Problem (EPP) aims to efficiently acquire energy resources. In the literature, existing approaches for energy-aware scheduling neglect to procure energy from sources such as an uncertain dynamic energy market, RES, and ESS. We aim to close this research gap and propose a two-level approach based on a memetic Non-dominated Sorting Genetic Algorithm (NSGA-III) and linear programming with the goal of minimizing the makespan, energy costs, and emissions of a schedule, incorporating dynamic energy prices and emissions, RES, and ESS. We evaluate the approach in computational experiments using FJSP benchmark instances from the literature as part of a rolling horizon approach with real energy market data. We investigate the impact of RES and ESS by presenting estimated Pareto fronts, showing potential savings in energy cost and carbon emissions.

Burmeister, S. C., Guericke, D., & Schryen, G. (2025) A two-level approach for multi-objective flexible job shop scheduling and energy procurement. *Cleaner Energy Systems*. <https://doi.org/10.1016/j.cles.2025.100178>



## 9 Comparative Analysis of Evolutionary Algorithms for Energy-Aware Production Scheduling

**Abstract.** The rise in renewable energy generation necessitates balancing energy supply and demand. Energy-aware production planning helps manufacturers align demand with dynamic grid conditions, reducing costs and emissions while supporting renewable integration. This is modeled as a multi-objective scheduling problem that balances traditional metrics like makespan or required workers with energy-related goals. Given the NP-hardness, multi-objective nature, and market dynamics of the problem, evolutionary algorithms are commonly applied to energy-aware scheduling. However, the literature mainly examines single algorithms, offering few direct comparisons between different methods. This study adapts NSGA-III, HypE, and  $\theta$ -DEA as memetic metaheuristics to minimize makespan, energy costs, emissions, and the number of workers, within a real-time energy market context. These adapted metaheuristics present different approaches for environmental selection. In a comparative analysis, we compare their solution quality using benchmark instances and real energy market data, and estimate upper bounds via exact methods.

Burmeister, S. C., Rogalski, T. N., & Schryen, G. (2025) Comparative analysis of evolutionary algorithms for energy-aware production scheduling. *Large-Scale Scientific Computations*



Part III  
Conclusion



## 10 Conclusion

This chapter synthesizes the contributions of the individual papers. Section 10.1 revisits the research questions and Section 10.2 discusses their implications. Section 10.3 addresses the limitations of the studies and concludes with potential avenues for future research.

### 10.1 Revisiting the Research Questions

This section revisits the research questions of this thesis and summarizes the findings of the studies conducted in Part II. Table 10.1 provides an overview of all research questions, their corresponding findings, and the related studies.

In the field of network design problems, the research question of *how scenario characteristics affect the model's computational solution time* (RQ1) is addressed by study P1. It introduces a novel mixed-integer linear optimization model that enables the application of exact solution methods for realistic large-scale distribution networks. The model integrates empirical requirements derived from literature and expert discussions. To analyze the model's behavior depending on various problem instance characteristics, the study conducts extensive computational experiments and a sensitivity analysis to identify correlations between model parameter values and the time required to solve instances optimally. The results reveal that the combination of the number of buses, lines, and the defined action scope significantly impacts computation time. Conversely, an increased number of available transformers improves the model's solvability.

In the area of energy-aware production planning, P2, P3, P4, and P5 consider the research question RQ2: *How can a multi-objective memetic algorithm optimize makespan and energy cost for energy-aware scheduling under the influence of dynamic real-time energy tariffs?* To address this question, P2 first presents a linear optimization model that incorporates dynamic energy costs within an FJSP framework. P2 demonstrates that the memetic NSGA-II detects price reductions under dynamic tariffs and uses waiting times without deteriorating the makespan. It enables decision-makers to select from a diverse Pareto front: short makespans incur high energy costs, while longer makespans allow for cost savings. The algorithm also identifies cost-saving idle times without necessarily increasing the makespan, thereby supporting flexible and preference-driven scheduling. Building on this foundation, P3 proposes a novel MA inspired by the NSGA-III to simultaneously minimize makespan and energy costs. Computational experiments evaluate the

Table 10.1: Research questions of this thesis

RQ	Findings	Study
RQ1	The combination of the number of buses, lines, and the defined action scope significantly impacts computation time. More available transformers improve solvability.	P1
RQ2	The memetic algorithm generates adaptive and economically efficient compromise solutions under real-time pricing conditions. It leverages price dynamics effectively without unnecessarily increasing the makespan.	P2, P3, P4, P5
RQ3	Objective prioritization leads to clear trade-offs: emphasizing emissions or energy cost reduction significantly extends the makespan. These effects are quantifiable and can be used to guide decision-making based on preferences.	P2, P3, P4
RQ4.1	Seasonal fluctuations strongly influence the opportunities for reducing emissions and costs—through both dynamic market tariffs and weather-dependent self-generation.	P3, P4
RQ4.2	Decision-makers have substantial control: depending on the available time flexibility or sustainability goals, key performance indicators can be deliberately influenced.	P2, P3, P4
RQ4.3	The results demonstrate that cost- or emission-oriented production strategies can be implemented in practice with only moderate adjustments to production plans – especially when strategic flexibility exists.	P2, P3, P4, P5
RQ5	Depending on the problem structure, certain designs prove more suitable. For example, memetic Hypervolume Estimation Algorithm for Multiobjective Optimization (MHypE) generally achieves the best distribution, while memetic Non-dominated Sorting Genetic Algorithm III (MNSGA-III) performs well in terms of solution quality.	P5

algorithm’s performance, demonstrating its ability to generate effective trade-offs between these objectives. P3 and P4 show that a moderate extension of the makespan leads to disproportionately high savings in energy costs. P5 highlights that MAs produce evenly distributed, high-quality Pareto fronts.

Regarding the research question of *how scheduling decisions that prioritize one objective — makespan, energy cost, or emissions — affect the others* (RQ3), study P2, P3 and P4 apply MAs to systematically investigate the effects of targeted

prioritizations. In P2, longer makespans result in significantly lower energy costs. P3 confirms that extending the makespan yields greater savings in costs and emissions than the use of expensive green energy. The findings indicate that even a slight increase in the makespan can result in considerable reductions in both energy costs and emissions, with energy cost savings generally exceeding those in emissions. Prioritizing one objective – makespan, energy cost, or emissions – affects the others; small increases in makespan can reduce energy costs and emissions, though savings differ. P4 shows that optimizing for objectives such as emissions or energy costs has substantial impacts on other objectives, particularly makespan. Moreover, while emissions can be lowered by accepting higher energy costs, the savings achieved through increased makespan are less substantial compared to those attainable by enhancing production flexibility.

The three-part research question of *how different seasonal conditions affect potential savings in energy cost and emissions* (RQ4.1), *to what extent decision-makers can influence the makespan, energy cost, and emissions of schedules* (RQ4.2), and *how feasible energy costs and emission-based schedules are for practice* (RQ4.3) is addressed by studies P2, P3, P4, and P5:

Regarding RQ4.1, P3 demonstrates that concentrating production on individual days with favorable prices yields substantial benefits. The frequency of such favorable prices varies across seasons, with higher availability of solar and wind energy in spring and summer significantly reducing energy costs and emissions. P4's main contribution is a multi-objective scheduling approach that minimizes makespan, energy cost, and emissions while accounting for energy market uncertainties, renewable energy, and storage. In this context, it highlights the importance of weather-dependent on-site energy generation (e.g., wind or solar) for selecting production time windows. The scope of the analysis is limited to a fixed configuration of storage and renewable energy systems. As such, it does not account for the potential variation in effects that may arise from different types or capacities of these systems, which could offer additional insights into the robustness and generalizability of the observed results.

Regarding RQ4.2, decision-makers influence scheduling outcomes by selecting different trajectories within the rolling horizon framework. P2 demonstrates how different decision priorities (e.g., lower makespan vs. lower costs) can be specifically implemented. P3 quantifies savings depending on the flexibility of decisions (e.g., +5% makespan). P4 shows that decision trajectories lead to significantly different objective values, such that decision-makers can influence makespan, cost, and emissions via trajectory selection in a rolling horizon approach. Trajectories such as a prioritization of makespan result in a balanced production schedule, whereas focussing on energy cost and emissions lead to more dynamic fluctuations.

Regarding RQ4.3, the proposed approach generates feasible schedules that reflect

varying decision-maker preferences, demonstrating that energy cost and emission-based schedules can be practically implemented. The proposed MAs produce feasible, implementable schedules reflecting various decision-maker preferences. P2 presents realistic use scenarios (e.g., production only on favorable days), while P3 discusses realistic adjustments of prices for emission reduction. P4 and P5 demonstrate technical feasibility through algorithmic stability and robust fronts. The approach provides a range of possible schedules, offering decision-makers flexibility in real-world applications.

The research question RQ5 investigates *how the various MOEAs differ in terms of solution efficiency and quality across different scenarios*. Study P5 presents a comparative analysis of the memetic adaptations of NSGA-III,  $\theta$ -DEA, and HypE, that are selected due to their different design paradigms. The findings show that all tested MOEAs produce competitive results, with significant differences in GD+, HV, and Spacing. Each algorithm succeeds in dominating parts of the reference set, whereas exact methods fail to identify optimal solutions within the given runtime due to the complexity of the problem. memetic Hypervolume Estimation Algorithm for Multiobjective Optimization (MHypE) usually offers the best distribution, while memetic Non-dominated Sorting Genetic Algorithm III (MNSGA-III) performs well in solution quality. These results suggest that HypE's search strategy is particularly well-suited for the problem instances under consideration. While the statistical significance supports the validity of the observed differences, research question RQ5 cannot yet be fully answered. The current analysis is based on only eight instances, which is insufficient to draw robust conclusions about the general performance of the investigated MOEAs. Moreover, the study does not account for different parameter configurations of the algorithms or the variability and uncertainty inherent in the performance metrics (e.g., Modified Generational Distance (GD<sup>+</sup>), Modified Inverted Generational Distance (IGD<sup>+</sup>), or spacing). To enable a more comprehensive and generalizable assessment of solution efficiency and quality, further experiments involving a broader set of instances, as well as sensitivity analyses with respect to algorithm parameters and evaluation metrics, are necessary.

## 10.2 Implications for Research and Practice

The evaluation of the research questions presented in the contributions of Part II leads to implications for research and practice. These implications address different stakeholders, including researchers, network planners, energy consumers, regulators, and society. Table 10.2 provides an overview of the formulated implications, which are further detailed in the following subsections.

Table 10.2: Implications of this thesis

#	Stakeholder	Implication	Study
1	Researchers	Linear optimization techniques are valuable for large-scale distribution network optimization	P1
2	Researchers	Scenario properties impact computational times and can be used to guide instance decomposition	P1
3	Researchers	Models should adapt to dynamic energy prices and emissions	P2, P3
4	Researchers	Rolling horizon approach is a suitable method to account for uncertain dynamic energy prices and emissions	P4
5	Researchers	Tailored search strategies can effectively address complex scheduling problems	P5
6	Network planners	Linear optimization methods can solve large-scale networks and help to ensure a reliable design through scenario analysis	P1
7	Energy consumers	Flexible production successfully plans minimize economic and ecological objectives	P2, P3, P4
8	Energy consumers	Optimizing energy procurement (RTP tariffs, RES generation, ESS utilization) significantly increases the minimization of energy cost and emissions in the face of uncertainty	P2, P3, P4
9	Regulators	Regulators should create incentives for flexible energy usage with dynamic tariffs	P2, P3, P4
10	Regulators	Incentives should help consumers to balance energy costs and emissions, and economic goals for sustainable energy demand	P3, P4
11	Regulators	Supporting the integration of RES and ESS strengthens grid stability and supports emissions reduction	P4
12	Society	Promoting flexible energy consumption increases sustainably generated energy use	P2, P3, P4
13	Society	A flexible energy demand with dynamic tariffs and the use of RES and ESS helps balance supply and demand effectively, lowering the need for infrastructure reinforcements	P1, P2, P3, P4

### 10.2.1 Implications for Research

In the area of network problems, the model in study P1 represents the nonlinear decision variables of current (amperes), voltage (volts), and power (watts) in a linear mixed-integer formulation. Based on the results, P1 identifies two main implications for research:

(1) First, the findings emphasize the relevance of linear optimization techniques for DNEP. Formulating the energy network with its nonlinear power flows as a specialized linear MCF results in efficiency gains. Supported by extensive simulations which underline the validity of this approach, the results suggest that a linear approach could be a promising direction for enhancing scalability in future research, as a linear model allows for the consideration of significantly larger networks compared to those examined in the existing literature.

(2) Second, the analysis of scenario properties provides valuable insights into their impact on computational times. This understanding allows researchers to better anticipate computational challenges and design experiments or algorithms that more effectively account for these influential factors. These insights can be utilized to decompose large-scale distribution networks into manageable subproblems when analyzing the entire network becomes too complex for the solution method to produce results within a reasonable time frame. It is also conceivable to develop problem-reduction techniques that construct a smaller network with similar characteristics based on a given network. Such methods are particularly useful in applications like the optimization of water distribution systems, for example, in the work of Hallmann and Suhl (2016).

In the area of scheduling problems, P2, P3, P4, and P5 adapt, implement and evaluate a range of multi-objective optimization algorithms to solve complex energy-aware scheduling problems.

(3) The research work P2 and P3 show that it is essential to develop models that can adapt to dynamic energy prices and fluctuating emissions. They show that MOEAs are suitable methods to addressing complex, energy-aware scheduling problems with real-world energy market data to ensure that energy-intensive consumers can make decisions that balance conflicting objectives. These EAs evaluated balance multiple competing objectives, like minimizing both energy costs and makespan in P2, and enable decision-making in dynamic environments like energy markets where exact methods failed to find optimal solutions within practical runtime limits, as shown in P4.

(4) By enabling iterative adjustments in scheduling and procurement decisions, applying these frameworks can lead to more flexible production planning models, which would be particularly valuable in industries facing significant energy market volatility. Study P4 shows that optimization models should incorporate flexibility with respect to uncertain dynamic energy pricing and emissions fluctuations.

Employing a Rolling Horizon approach addresses uncertainties in dynamic energy prices and emissions by enabling adaptive decision-making over time. In light of the challenges posed by difficult-to-predict energy prices and emissions, it becomes evident that the possibility of a rolling planning approach successfully supports the decision-making process over time. As an a posteriori approach, it supports decision-makers to continuously reassess trade-offs, offering targeted support for transforming production in an energy-cost-efficient and sustainable manner.

(5) Tailored search strategies, such as those used in P5, can effectively address complex energy-aware scheduling problems, but their performance may vary depending on the problem characteristics. Integrating local refinement strategies as in P2 and P3 leads to more effective decision-making tools for energy-aware scheduling. This underscores the importance of carefully selecting and configuring algorithms to match the specific requirements of the given instance, as no single method consistently outperforms others across all scenarios.

### 10.2.2 Implications for Network Planners and Manufacturers

Implications for network planners arise from research work P1, as it deals with network planners as decision-makers and offers insights into the impact of scenario characteristics on computation times.

(6) First, one implication is that network operators can solve large-scale networks through linear optimization. They should incorporate uncertainties regarding future energy consumption developments into their planning processes to ensure a future-proof and efficient network infrastructure. To achieve this, appropriate scenario analyses can be designed to efficiently utilize available temporal and computational resources, while still deriving well-founded and cost-effective expansion strategies for their distribution networks.

In the area of energy-aware production planning, studies P2, P3, and P4 demonstrate that manufacturers can achieve substantial cost savings and emission reductions through intelligent and flexible energy consumption management.

(7) Another implication is that manufacturers can benefit from flexible production plans that minimize both economic and ecological objectives. By applying algorithms such as MOEAs, manufacturers can dynamically adjust their production processes to fluctuating energy prices and emissions. The ability to select a production plan from a set of solutions a posteriori offers manufacturers the flexibility to tailor production plans according to their specific goals and priorities. This not only enables cost savings but also fosters more sustainable production practices.

(8) A further implication highlights the optimization of energy procurement in the face of uncertainty. By considering dynamic RTP tariffs, dynamic energy emissions, and integrating technologies such as behind-the-meter RES and ESS, manufacturers can reduce both their energy costs and emissions. Additionally,

through the implementation of rolling planning, manufacturers can continuously adjust their production and energy procurement strategies to dynamic energy prices, aligning energy demand with current market conditions. This leads to a more flexible and efficient production process, assisting manufacturers in optimizing their energy procurement strategy and responding flexibly to seasonal or daily price fluctuations.

### 10.2.3 Implications for Regulators

While this thesis provides implications for network planners and manufacturers in Sections 10.2.2, it also addresses regulatory authorities as they play a crucial role in shaping the future development of the energy system through regulations and guidelines. Therefore, also insights for regulators can be drawn from the findings of this thesis.

(9) First, regulators should create incentives that promote flexible energy usage. Dynamic electricity tariffs such as RTP can be an effective tool for managing energy consumption as the results of P2, P3, and P4 suggest. Since energy-intensive companies can reduce their energy costs by shifting energy-intensive processes to periods with lower tariffs, targeted measures to encourage flexible load management could make overall energy consumption more efficient and improve grid stability. This is consistent with the conclusion of Panda et al. (2023), who argue that DSM techniques address challenges such as high energy production costs during peak periods, as well as issues related to reliability, security, and congestion management at both generation and distribution system levels.

(10) A second implication is that energy consumers like manufacturers are confronted with a clear trade-off between costs, emissions, and economic goals (e.g., makespan or workforce) as shown in papers P3, P4, and P5. To strengthen sustainable over cost-saving energy demand, regulators could develop policies that help consumers balance these competing objectives sustainably – such as support programs for energy-efficient technologies or emissions trading schemes that reward emission reductions.

(11) A third implication is that integrating renewable energy sources and energy storage systems can substantially enhance grid stability and reduce emissions, as demonstrated in paper P4. Regulators can support the advancement of these technologies by introducing targeted investment incentives or tax benefits. In turn, this approach could reduce peak loads of the grid, as highlighted in other studies (e.g., Azim et al. (2024) and Bhattarai et al. (2016)) and therefore mitigate the anticipated costs of grid expansion, since less capacity is needed.

#### 10.2.4 Implications for Society

While studies P1 to P5 was conducted within a framework where network operators and production planners act as decision-makers, the findings also yield broader implications for society. The research contributes to enhancing sustainability and climate protection while simultaneously addressing economic considerations.

(12) Society can benefit from flexible energy consumption as this could encourage the use of sustainably generated energy. By shifting energy demand to periods when renewable energy generation is abundant, such as during sunny or windy periods, this would maximize the use of sustainably generated energy. This implication is in line with the conclusion of other studies, such as the work of Zeng et al. (2013), which indicates that DR facilitates a closer alignment of electricity consumption with the production patterns of renewable distributed generation, while integrated planning has shown to produce amplified environmental benefits. This practice not only supports the integration of renewable energy into the grid but also contributes to reducing reliance on fossil fuels, making the energy system cleaner and more resilient, and accelerating progress towards carbon neutrality.

(13) A final implication is that the use of dynamic tariffs and flexible energy consumption help balance energy supply and demand more effectively. This corroborates with previous studies such as the work of Albadi and El-Saadany (2008), who conclude that DR programs can reduce overall electricity prices, improve system reliability, and reduce price volatility. An improved system reliability, in turn, could lower the need for infrastructure reinforcements and associated costs, benefiting society by reducing the financial burden of upgrading energy distribution networks.

### 10.3 Limitations & Avenues for Future Research

The studies in Part II make a comprehensive contribution to the development of robust and efficient approaches for energy-oriented optimization problems. They cover a wide range of challenges from the problem domains of distribution network expansion planning and energy-aware production planning. Nevertheless, the studies have certain limitations, which are outlined in this section and from which avenues for future research are derived.

One limitation of this research is the restricted use of real-world data in the conducted studies. In the investigation of energy networks (P1), distribution networks are generated based on empirical data, with network components assigned characteristics reflecting real-world conditions. For the analyses on energy-aware production scheduling (P2–P5), benchmark datasets for FJSP problems are employed, supplemented by real energy market data. Future research could enhance empirical validation by applying the developed methods to real energy networks or

actual production orders. The use of real-world data would allow for a more precise evaluation of cost savings in distribution network expansion, as well as trade-offs between cost and emission reductions in production planning. Additionally, key performance metrics such as return on investment could be calculated more reliably.

Another limitation concerns the absence of a comprehensive automated algorithm configuration for the applied metaheuristic solution methods. While different parameter configurations are tested to prevent the selection of an excessively poor configuration by chance (cf. P2), this approach does not replace the systematic use of a parameter optimization. Parameter optimization is omitted in this study since it is particularly suitable for repetitive problems – such as when decision-makers apply the algorithm to a target scenario that is similar to the one for which the default parameter settings have been designed (Stützle & López-Ibáñez, 2019). However, in this research, a diverse set of benchmark instances is considered. Parameter tuning would be especially relevant in combination with real-world data, as it would then be possible to optimize solutions for recurring planning problems over time. Future studies could extend empirical investigations by analyzing parameter selection and assessing its impact on solution quality.

The formulated models in this research are designed to address the specific scope of each study, focusing on particular requirements while omitting certain operational constraints. For instance, in the domain of energy transport, some studies integrate ESS (Sabzehgar et al., 2021; Yi et al., 2022) as a controllable instrument for network operators, whereas in study P4, such systems are only considered from the consumer perspective. Similarly, in production scheduling, existing studies incorporate additional constraints that are not considered in this research, such as time windows including release and due dates (Tadumadze et al., 2020), sequence-dependent setup times and machine operator qualifications (Kress et al., 2019), or factors like machine maintenance (Geurtsen, Adan, & Akçay, 2023). Future studies could extend the presented approach by incorporating such practical constraints to evaluate how additional real-world limitations affect the degrees of freedom in energy-aware scheduling and to what extent they restrict the potential for optimization.

A further limitation lies in the isolated perspective adopted in this research. While the studies focus on individual decision-makers, such as network operators or industrial production planners, future research could place greater emphasis on the interplay between different stakeholders. Game-theoretic approaches could be used to analyze strategic interactions, for example, between producers competing for low-cost energy and network operators ensuring grid stability. Such approaches have been explored in the literature, particularly in bidding models, where limited capacity is available in a dynamic market (Ranaboldo et al., 2024). The metaheuristic methods developed in this thesis could be leveraged to provide rapid

decision support, guiding production planners determine up to which price level energy purchases remain economically viable. Similarly, in distribution network optimization, flexibility markets could be incorporated to support network operators in investigating how coordinated load shifting and energy storage utilization contribute to grid stability. Future research could deepen the understanding of stakeholder interactions and propose new mechanisms for improved coordination in energy systems.



Part IV  
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