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Multiobjective Optimization Model for Elevator Call Allocation

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Abstract

The performance of an elevator system is often perceived through direct metrics of passenger service level, but the climate crisis creates an increasing need to consider energy efficiency as an integral element of performance. The performance of an elevator group is highly dependent on its control method. A central part of elevator group control is the call allocation system that is responsible for determining the best car to serve each call.

This thesis develops a multiobjective optimization model for call allocation with three objectives: energy consumption of the elevator group, time to destination of passengers, and waiting time. An achievement scalarizing value function is formulated to transform the multiobjective optimization problem to a single objective problem. Decision maker preferences are included in the value function as a reference point that is adjusted based on traffic intensity. The single objective problem is solved with the same genetic algorithm already used in the production version of the KONE call allocation system. The performance of the new call allocation method is tested with simulations in three different elevator groups.

In the simulations, overall energy consumption is reduced 4–20% depending on the elevator group. Waiting time increased in the smallest elevator group by 5% but decreased in the other two groups by 10% and 19%. The reductions in these two objectives came at the cost of a 3–11% increase in time to destination. The behavior of the system follows known preferences on a general level, with most energy consumption reductions, and increases in time to destination, occurring in low traffic. These results are sufficient for a proof of concept, but additional testing and development is recommended before considering deployment. Work on preference elicitation is recommended to improve the possibilities for further development of call allocation methods.

Keywords Achievement scalarizing function, multiobjective optimization, energy consumption, call allocation, elevator traffic

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Tiivistelmä

Hissijärjestelmän suorituskyky hahmotetaan usein yksinomaan asiakkaiden palvelutasoon liittyvien mittareiden kautta. Ilmastokriisi kuitenkin luo kasvavan tarpeen sisällyttää energiatehokkuus keskeiseksi osaksi suorituskyvyn mittaristoa. Hissiryhmän suorituskyky riippuu olennaisesti ryhmän ohjauksesta. Keskeinen osa tätä ohjausta on hissikutsujen allokointijärjestelmä, jonka vastuulla on määrittää paras hissikori palvelemaan kutakin kutsua.

Tämä diplomityö kehittää kolmen tavoitteen monitavoiteoptimointimallin hissikutsujen allokointitehtävälle. Mallin kolme tavoitetta ovat hissiryhmän energiankulutus sekä matkustajien matkustus- ja odotusajat. Tämä monitavoiteoptimointiongelma muunnetaan yhden tavoitteen ongelmaksi muotoilemalla sille saavutukset skalarisoiva arvofunktio. Päätöksentekijän mieltymykset sisällytetään arvofunktioon vertailupisteenä, jota säädetään liikenneintensiteetin perusteella. Yhden tavoitteen ongelma ratkaistaan geneettisellä algoritmilla, joka on käytössä KONEen hissikutsujen allokointijärjestelmän tuotantoversiossa. Kehitetyn allokointimenetelmän suorituskykyä testataan simuloinneilla kolmessa eri hissiryhmässä.

Suoritetuissa simuloinneissa kokonaisenergiankulutus laskee 4–20% hissiryhmästä riippuen. Odotusaika nousee pienimmässä hissiryhmässä 5%, mutta laskee kahdessa muussa ryhmässä 10% ja 19%. Näiden kahden tavoitteen alentamisen kustannus on 3–11% nousu matkustusajassa. Järjestelmän toiminta noudattaa tunnettuja päätöksentekijän mieltymyksiä yleisellä tasolla: suurin osa energiankulutuksen alenemisesta ja matkustusajan noususta tapahtuu hiljaisen liikenteen aikana. Nämä tulokset ovat riittäviä osoittamaan käytettyjen menetelmien toimivuuden, mutta laajempaa testausta ja kehitystyötä suositellaan ennen kehitetyn järjestelmän käyttöönoton harkitsemista. Päätöksentekijän mieltymysten tarkempaa kartoittamista suositellaan edellytysten luomiseksi entistä parempien hissikutsujen allokointimallien kehitystyölle.

Avainsanat Saavutukset skalarisoiva funktio, monitavoiteoptimointi, energiankulutus, kutsujen allokointi, hissiliikenne

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Otaniemi, 24.5.2021

Tapio Hautamäki

Contents

Symbols and abbreviations

Symbols

$\mathbb{R}^n$	n-dimensional Euclidian space
$\boldsymbol{x}$	Decision variable vector
f_i	Objective function
k	Number of objective functions
S	Feasible region
Z	Feasible objective region, set of all possible outcomes
$\boldsymbol{f}(\boldsymbol{x}), \boldsymbol{z}$	Objective vector
$\bar{z}_i$	Aspiration level
$\bar{\boldsymbol{z}}$	Reference point
$\boldsymbol{z}^{\star}$	Ideal objective vector
$\boldsymbol{z}^{\star\star}$	Utopian objective vector
$\boldsymbol{z}^{\text{nad}}$	Nadir objective vector
$\mathbb{R}^n_+$	Nonnegative orthant of $\mathbb{R}^n$
$\mathbb{R}^n_\epsilon$	Blunt cone in $\mathbb{R}^n$
E	Energy consumption objective function
T	Time to destination objective function
W	Waiting time objective function

Operators

$\succcurlyeq$	Preference relation between performance levels
$\succcurlyeq_d$	Preference relation between changes in performance levels
$\sim$	Indifference between performance levels
$\sim_d$	Indifference between changes in performance levels
int	Interior

Abbreviations

DM	Decision maker

Chapter 1

Introduction

An elevator system is a key element in the functionality of tall buildings. In large buildings the system has several elevator groups. An elevator group consists of nearby elevator shafts with cars moving inside them, and landings in the floors along the way. Landings have call giving devices close to the elevator doors. The elevators of a group share the same call giving devices. In modern elevators these devices have an option for each destination floor instead of the directions 'up' or 'down'. Each elevator group has one computer that serves as a group controller.

A user of a modern elevator group orders an elevator car by indicating their destination floor with a call giving device. The user is shown the elevator that will answer the call and they can immediately move to the correct doors. After some waiting time, an elevator destined for the desired direction arrives on the landing, and the transit begins. During the transit the elevator car may stop at other landings along the way. At the destination floor, the passenger exits the car, completing the journey.

The performance of an elevator group is usually perceived as some metric directly related to passenger service quality (see e.g. Al-Sharif et al., 2015; Hirasawa et al., 2008; Jamaludin et al., 2010). The rapidly escalating climate crisis creates an increasing need to consider energy efficiency as an integral element of performance. Efficient operation of an elevator group is highly dependent on the way it is controlled. The elevator company KONE has a long history of research and development in group control methods (see e.g. Alander et al., 1995; Siikonen, 1997; Siikonen & Ylinen, 2006). KONE's current production version provides excellent results in terms of passenger service level, but optimization of energy consumption is not in industrial production despite some promising test results (Tyni & Ylinen, 2006).

The group controller is responsible for deciding the best route for each elevator car. With many cars and calls, this creates a complex routing problem.

To simplify the problem, the current practice is to determine the routing of a single elevator with heuristics (Tyni & Ylinen, 2001). Now the group controller must decide only which car answers which call. This reduced problem is called a call allocation problem (Ruokokoski et al., 2016). Usually the objective in solving the call allocation problem is related to the swiftness of transportation (see e.g. Bolat et al., 2013; Tyni & Ylinen, 2001; Valdivielso & Miyamoto, 2011). The current KONE call allocation system utilizes two objectives, passenger waiting time and time to destination. The preferences between the objectives are modeled with an additive value function. Even though an additive value function has been considered appropriate for modeling preferences between these two objectives, it may not be sufficient when energy consumption is also considered.

This thesis develops a multiobjective optimization model for the call allocation problem with three objectives: 1) waiting time and 2) time to destination of passengers as well as 3) energy consumption of elevators. The existing group control is modified to add the energy consumption objective. The three objectives are conflicting, so tradeoffs must be made between them. To determine the best tradeoffs, decision maker input is needed. It is not possible to get this input during optimization, because allocation decisions must be made quickly with the elevators constantly running. Therefore, the problem is reduced to a single objective optimization problem, where decision maker preferences are included in the value function. This single objective problem is then solved with the same genetic algorithm already in use in the existing group control (Tyni & Ylinen, 2001). The optimization model is validated in a simulation environment to assess and visualize its performance in different buildings and traffic situations.

The remainder of this thesis is structured as follows. Chapter 2 includes the basic concepts of elevator traffic, discussion of preference modeling and theory of multiobjective optimization. Chapter 3 introduces the optimization model implemented in this thesis. Chapter 4 presents the simulation results and discusses potential for further development. Chapter 5 concludes the thesis by summarizing the main contributions and recommending future research.

Chapter 2

Background

This chapter provides theoretical background and insights about the nature of the optimization task at hand. We begin with key concepts of elevator traffic. We discuss typical traffic situations, rules of elevator control, and definitions of timespans of special interest in an elevator journey. In Section 2.2 we move on to discuss requirements and preferences the optimization model should meet. Possibilities and limitations of an additive value function are highlighted. Section 2.3 introduces the theory of multiobjective optimization.

2.1 Basic concepts of elevator traffic

Dr Gina Barney and Dr Lutfi Al-Sharif, two veterans of elevator traffic design, describe the components of elevator traffic in *Elevator traffic handbook: theory and practice* (Barney & Al-Sharif, 2015, pp. 73-77). There are three distinct traffic components: incoming, outgoing and interfloor traffic. Incoming traffic consists of passengers entering the building at the entrance floor and traveling to destinations on the upper floors of the building. When the dominant, or only, traffic component is incoming, the situation is called an up peak traffic condition. In typical office and public buildings, up peak occurs in the morning. It is considered the most challenging situation for an elevator system. Typically, if an elevator system can efficiently handle the morning up peak, it can also handle other traffic conditions. Outgoing traffic is the opposite of incoming, consisting of passengers traveling down to the entrance floor from upper floors. When outgoing traffic is the dominant, or only, component, the situation is called a down peak traffic condition. In an office building, down peak occurs at the end of the working day. In addition to up and down peaks, lunchtime has a discernible traffic pattern. It is typical for a lunchtime traffic condition that there is a dominant traffic flow to and from a specific floor, most commonly the entrance floor. Interfloor traffic consists of passengers traveling between different floors of the building in both directions. It can be considered the main traffic component when no discernible pattern can be detected.

Efficient routing of a group of elevators is generally a very complex optimization task (Tyni & Ylinen, 2001). Computing time is also limited because the solution needs to be ready and decided for a new passenger shortly after they give a call. To cope with these limitations, the prevailing practice is to determine the routing of a single car with a heuristic method called the collective control principle (Tyni & Ylinen, 2001). It dictates the six rules below (Barney & Al-Sharif, 2015, p. 239). Here the term 'landing call' refers to a landing with a passenger waiting to be picked up, the term 'car call' to a destination landing for a passenger inside the car, and the term 'call' to either of those two. Landing call direction refers to the direction of travel of the passenger at that landing.

1. A car serves the calls in floor sequence in its direction of travel.
2. If a landing call direction is opposite to the car's direction, the landing call is bypassed.
3. If a car is full, it bypasses landing calls until there is space for new passengers.
4. If the only calls left in a car's direction of travel are landing calls with opposite direction, the car moves to the furthest landing call and changes direction there.
5. If there are no more calls in a car's direction of travel, the car changes direction.
6. If there are no more calls anywhere, the car remains stationary until it starts moving in the direction of the first new call.

As this method is used for controlling a single car, the problem for determining the routes for an elevator group reduces to a problem of allocating calls to cars within the group.

2.1.1 Traffic definitions

There are a few globally established definitions for elevator traffic. Barney et al. (2005) were instrumental in unifying the most central definitions introduced here. Journey time is the time from passenger arrival to the moment when the passenger alights the car at the destination floor. Time to destination is the time from passenger arrival to the moment when their elevator car starts to open its doors at the destination floor. Waiting time is the time from passenger arrival to the moment when their elevator car begins to open its doors at the boarding floor. After this, the transit time begins, ending when the elevator car doors start opening at the destination floor. We can see that time to destination is the sum of waiting time and transit time.

Waiting time can be further divided to walking time and standing time at the moment when the passenger stops to stand in front of the elevator allocated for them. Call time is defined for conventional call-giving devices (Sorsa, 2002). It is the time from registering a new call until the moment when the call is cancelled. Usually a call is cancelled automatically when a responding elevator car starts slowing down at the boarding floor. Interval is the average time between successive lift car arrivals (or departures) at the main terminal floor (Barney & Al-Sharif, 2015, p.81). Figure 2.1 illustrates these definitions and their relationships to one another.

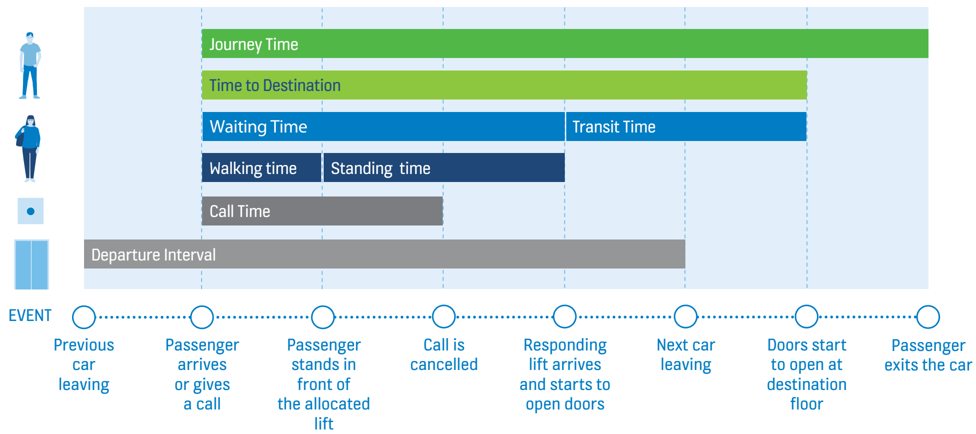

Figure 2.1: Definitions of timespans in elevator traffic. Illustration by Siikonen (2020, p.9).

2.2 Requirements for the value function

In this section we discuss the preferences and requirements the developed model should fulfill. Currently the call allocation system at KONE utilizes an additive value function with waiting time and time to destination as attributes.

The value function is of the form

$$\alpha_W W + \alpha_T T, \tag{2.1}$$

where W is waiting time, T is time to destination, and α_W and α_T are weighting coefficients. A natural choice would be to extend the current value function by adding the energy consumption objective as a term $\alpha_E E$. Using an additive value function is quite common. Tyni and Ylinen (2006) proposed using it in their study of energy optimization in call allocation. Kim et al. (1998) also used an additive value function in their call allocation method based on fuzzy theory to solve a similar problem of three objectives. The first subsection reviews the theory of additive value functions. The applicability of this method with the added attribute of energy consumption is discussed in Section 2.2.2.

2.2.1 Theory of additive value functions

We will denote with $\succcurlyeq$ a preference relation between performance levels of an attribute. With this notation, $a \succcurlyeq b$ means that level a is at least as preferable as b. Let Z be the set of all possible multi-attribute outcomes of a decision problem, and Z_i the set of all possible outcomes for the attribute i. We can partition the set Z in two by denoting a subset of indices with I. Set Z_I is the set of attributes with indices in I, and $Z_{I^\complement}$ is the set of all other attributes. Thus, we have $Z_I \cup Z_{I^\complement} = Z$. We need this notation to define two important concepts in the theory of additive value functions, preferential independence, and difference independence.

Definition 2.2.1. (Dyer & Sarin, 1979). Z_I is preferentially independent of $Z_{I^\complement}$ if

$$\begin{aligned} & (z_I, z'_{I^\complement}) \succcurlyeq (z'_I, z'_{I^\complement}) \quad \text{for any } z'_{I^\complement} \in Z_{I^\complement} \text{ and } z_I, z'_I \in Z_I \\ \Rightarrow \quad & (z_I, z_{I^\complement}) \succcurlyeq (z'_I, z_{I^\complement}) \quad \text{for all} \quad z_{I^\complement} \in Z_{I^\complement}. \end{aligned}$$

Definition 2.2.2. (Dyer & Sarin, 1979). The attributes $Z_1, ..., Z_k$ are mutually preferentially independent if for every subset I of $\{1, .., k\}$ the set Z_I of these attributes is preferentially independent of $Z_{I^\complement}$.

Intuitively mutual preferential independence means that preferences between different levels of attributes do not depend on the levels of other attributes, if these other attribute levels are the same for all alternatives. We denote with $\succcurlyeq_d$ a preference relation between *changes* in performance levels of an attribute. With this notation, $(a \leftarrow b) \succcurlyeq_d (c \leftarrow d)$ means that a change from b to a is at least as preferable as a change from d to c. We denote indifference with $\sim_d$. It is defined as $(a \leftarrow b) \sim_d (c \leftarrow d) \Leftrightarrow (a \leftarrow b) \succcurlyeq_d (c \leftarrow d) \wedge (c \leftarrow d) \succcurlyeq_d (a \leftarrow b)$ (Dyer & Sarin, 1979). The concept of difference consistence gives us a relationship between the two preference relations, $\succcurlyeq$ and $\succcurlyeq_d$. Its rigorous definition is given in Dyer and Sarin (1979). Difference consistence is a simple property. Loosely speaking, it just means that preferences between attribute levels stay the same regardless of the route that is taken to reach those levels.

Definition 2.2.3. (Dyer & Sarin, 1979). The attribute Z_i is difference independent of $Z_{I^\complement}$, where $I = \{i\}$, if,

$$\text{for all } z_i, z_i' \in Z_i, \text{ such that } (z_i, z_{I^\complement}) \succcurlyeq (z_i', z_{I^\complement}) \text{ for some } z_{I^\complement} \in Z_{I^\complement},$$
$$(z_i, z_{I^\complement}') \leftarrow (z_i', z_{I^\complement}') \sim_d (z_i, z_{I^\complement}) \leftarrow (z_i', z_{I^\complement}) \text{ for any } z_{I^\complement}' \in Z_{I^\complement}.$$

Intuitively difference independence means that preference between changes in the level of an attribute does not depend on the levels of other attributes, if these other attribute levels are the same for both alternatives. We have now discussed all the necessary definitions for the following theorem, which describes an additive value function $V(\boldsymbol{z}) = \sum_{i=1}^{k} v_i(z_i)$, and the conditions for its use as an accurate representation of preference relations between attributes.

Theorem 2.2.1. *(Dyer & Sarin, 1979). Assume $k \geq 3$, $Z_1, ..., Z_k$ are mutually preferentially independent, difference consistent, and Z_1 is difference independent of $Z_{1^\complement}$. Then there exists functions $v_i : Z_i \to \mathbb{R}, i = 1, ..., k$, such that for all $z_i, z_i', z_i^\circ, z_i^\dagger \in Z_i$,*

i) if $z, z', z^\circ, z^\dagger \in Z$, then

$$z \leftarrow z' \succcurlyeq_d z^\circ \leftarrow z^\dagger \quad \Leftrightarrow \quad \sum_{i=1}^{k} v_i(z_i) - \sum_{i=1}^{k} v_i(z_i') \geq \sum_{i=1}^{k} v_i(z_i^\circ) - \sum_{i=1}^{k} v_i(z_i^\dagger);$$

ii) if $z, z' \in Z$, then

$$z \succcurlyeq z' \quad \Leftrightarrow \quad \sum_{i=1}^{k} v_i(z_i) \geq \sum_{i=1}^{k} v_i(z_i').$$

Proof. See Dyer and Sarin (1977) as cited in Dyer and Sarin (1979).

2.2.2 Call allocation preferences

Solutions to the call allocation problem must ultimately answer the needs of building managers. Building managers are responsible for answering the needs of tenants and communicating requirements to KONE. For the purposes of this thesis, the building managers are unreachable, so it is not possible to model their preferences accurately. However, KONE experts are able to provide some general estimates of the preferences of building managers. They are as follows.

1. When traffic is high, only time to destination matters, because this gives the best handling capacity for the elevator group.
2. When traffic is not high, the focus should be on minimizing energy consumption.
3. Waiting times should stay at a reasonable level at all times.

Let us denote with E, T, and W, respectively, energy consumption, time to destination, and waiting time. We will first consider if an extension of the existing additive value function could be used to capture the preferences. As suggested in the beginning of this section, we will extend the current value function introduced in Equation (2.1) by adding the energy consumption objective as a term $\alpha_E E$, and investigate the value function

$$V(E, T, W) = \alpha_E E + \alpha_T T + \alpha_W W,$$

where α_E, α_T and α_W are weighting coefficients.

Assume T_{high} is some level for time to destination that is so high that passengers are reaching their destinations much later than usual. Respectively, T_{low} is faster service than usual. Let us first consider a situation where $T = T_{\text{low}}$. We now have low traffic since the elevator system can handle the incoming traffic without any trouble. We should therefore act according to statement 2 and focus on minimizing energy consumption. Assume that we have an opportunity to reduce energy consumption by one unit at the cost of a moderate ΔT increase in time to destination. In this situation, the trade is accepted in accordance with statement 2. This means that the change is more preferable than no change, and we get

$$\begin{aligned}
&(E-1, T_{\text{low}} + \Delta T, W) \succ (E, T_{\text{low}}, W) \\
\Rightarrow &V(E-1, T_{\text{low}} + \Delta T, W) > V(E, T_{\text{low}}, W) \\
\Rightarrow &\alpha_E(E-1) + \alpha_T(T_{\text{low}} + \Delta T) + \alpha_W W > \alpha_E E + \alpha_T T_{\text{low}} + \alpha_W W \\
\Rightarrow &\alpha_T \Delta T > \alpha_E.
\end{aligned}$$

Let us then consider a situation where $T = T_{\text{high}}$. Now the elevator group is struggling to handle the incoming traffic, and we should act according to statement 1 to maximize handling capacity. Assume that we have the same opportunity to reduce energy consumption by one unit at the cost of a moderate ΔT increase in time to destination. In this situation, we should focus on minimizing time to destination in accordance with statement 1 and not accept the increase. This means that no change is more preferable, and we get

$$
\begin{aligned}
&(E-1, T_{\text{high}} + \Delta T, W) \prec (E, T_{\text{high}}, W) \\
\Rightarrow &\alpha_E(E-1) + \alpha_T(T_{\text{high}} + \Delta T) + \alpha_W W < \alpha_E E + \alpha_T T_{\text{high}} + \alpha_W W \\
\Rightarrow &\alpha_T \Delta T < \alpha_E,
\end{aligned}
$$

which is a contradiction. This shows that the preference relations between the three attributes E, T, and W cannot be accurately modeled with an extension of the existing additive value function. Other methods are needed.

One important consideration when choosing a method is the ease of preference modeling. Ideally there would be an intuitive method for each building manager to state their preferences by selecting some parameters or options in a user interface for the elevator system. Even though it is not in the scope of this thesis, the chosen method should allow further development in that direction. This thesis should provide a model where preferences can be adjusted by changing some parameters rather than trying to find the exact shape of the value function. The aim is to simplify the problem for the decision maker. It should also be possible to adjust the call allocation behavior continuously and robustly, meaning that small adjustments in preferences should lead to small and continuous adjustments in call allocation behavior.

The realm of multiobjective optimization provides tools for creating models where preferences are included as desirable or acceptable levels of attributes or in some other parametric form. KONE has experimented a multiobjective optimization method called the achievement scalarizing function a few years ago as a possible solution to fulfill the requirements discussed here, although fine-tuning the existing additive value function has been the main direction of development. Creating incremental changes to the existing model seems like an attractive alternative, despite its drawbacks. We will look at multiobjective optimization and especially achievement scalarizing functions in the next section.

2.3 Multiobjective optimization

This section provides an introduction to multiobjective optimization. We go through the concepts necessary for this thesis mostly based on the book *Nonlinear multiobjective optimization* by Miettinen (1999). The interested reader should definitely refer to the original work for a broader understanding on multiobjective optimization. The section begins by laying a foundation for understanding methods of multiobjective optimization. Section 2.3.1 introduces the central concepts and definitions needed, such as the concepts of a decision maker and Pareto optimality. In Section 2.3.2 we discuss the achievement scalarizing function approach.

2.3.1 Concepts

A multiobjective optimization problem is of the form

$$\begin{aligned} &\text{minimize} && \{f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), ..., f_k(\boldsymbol{x})\} \\ &\text{subject to} && \boldsymbol{x} \in S, \end{aligned} \tag{2.2}$$

where we have $k \geq 2$ objective functions $f_i : \mathbb{R}^n \to \mathbb{R}$, the decision variable vector $\boldsymbol{x} = (x_1, x_2, ..., x_n)^T$, and the feasible region S (Miettinen, 1999, p.5). In the following we denote the vector of objective functions $\boldsymbol{f}(\boldsymbol{x}) = f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), ..., f_k(\boldsymbol{x})^T$. The image of the feasible region $\boldsymbol{f}(S) = Z$ is called the feasible objective region. The elements of Z are called objective (function) vectors and denoted by $\boldsymbol{f}(\boldsymbol{x})$ or $\boldsymbol{z} = (z_1, z_2, ..., z_k)^T$, where $z_i = f_i(\boldsymbol{x})$ for all $i = 1, ..., k$ are objective (function) values (Miettinen, 1999, p.5).

The realm of multiobjective optimization deals with conflicting objectives. Therefore, it is not possible to find a solution that would be optimal for all objectives simultaneously (Miettinen, 1999, p. 11). Some solutions are still clearly better than others. Edgeworth (1881) defined a set of points such that movement in any direction would result in a deterioration of at least one value. This concept was later named after Vilfredo Pareto, who developed it further (see Pareto, 1896; as cited in Miettinen, 1999, p. 11). In our terminology, we are interested in solutions where further improvement in any objective would lead to deterioration in another. These are called Pareto optimal, noninferior or nondominated solutions (Miettinen, 1999, pp. 11-12). Miettinen (1999, p.11) defines Pareto optimality formally as follows.

Definition 2.3.1. A decision vector $\boldsymbol{x}^* \in S$ is Pareto optimal if there does not exist another vector $\boldsymbol{x} \in S$ such that $f_i(\boldsymbol{x}) \leq f_i(\boldsymbol{x}^*)$ for all $i = 1, ..., k$ and $f_j(\boldsymbol{x}) < f_j(\boldsymbol{x}^*)$ for at least one index j.

An objective vector $\boldsymbol{z}^* \in Z$ is Pareto optimal if there does not exist another vector $\boldsymbol{z} \in Z$ such that $z_i \leq z_i^*$ for all $i = 1, ..., k$ and $z_j < z_j^*$ for at least one index j. Equivalently, $\boldsymbol{z}^*$ is Pareto optimal if the decision vector corresponding to it is Pareto optimal.

Figure 2.2 illustrates Pareto optimal solutions. The set of all Pareto optimal objective vectors is called the Pareto optimal set (Miettinen, 1999, p.12). Next, we define two variations of Pareto optimality: weak Pareto

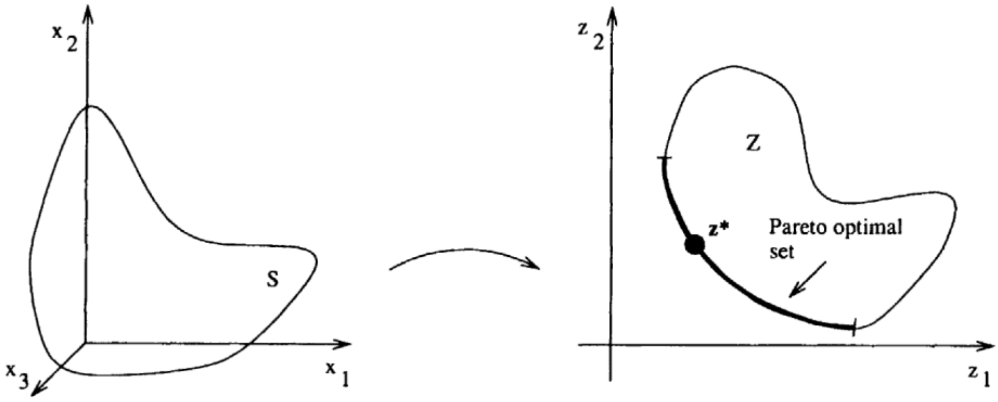

Figure 2.2: Illustration by Miettinen (1999, p.11), showing a feasible region $S \subset \mathbb{R}^3$ and its image, a feasible objective region $Z \subset \mathbb{R}^2$. All Pareto optimal objective vectors are on the thick line, with $\boldsymbol{z}^*$ as one example.

optimality and ϵ-proper Pareto optimality.

Definition 2.3.2. (Miettinen, 1999, p. 19). A decision vector $\boldsymbol{x}^* \in S$ is weakly Pareto optimal if there does not exist another vector $\boldsymbol{x} \in S$ such that $f_i(\boldsymbol{x}) < f_i(\boldsymbol{x}^*)$ for all $i = 1, ..., k$.

An objective vector $\boldsymbol{z}^* \in Z$ is weakly Pareto optimal if there does not exist another vector $\boldsymbol{z} \in Z$ such that $z_i < z_i^*$ for all $i = 1, ..., k$; or equivalently, if the decision vector corresponding to it is weakly Pareto optimal.

Definition 2.3.3. A decision vector $\boldsymbol{x}^* \in S$ and the corresponding objective vector $\boldsymbol{z}^* \in Z$ are ϵ-properly Pareto optimal if

$$(\boldsymbol{z}^* - \mathbb{R}^k_\epsilon \setminus \{\boldsymbol{0}\}) \cap Z = \emptyset,$$

where $\mathbb{R}^k_\epsilon = \{\boldsymbol{z} \in \mathbb{R}^k |\, \mathrm{dist}(\boldsymbol{z}, \mathbb{R}^k_+) \leq \epsilon \|\boldsymbol{z}\|\}$ is a blunt cone and $\epsilon > 0$ is a predetermined scalar (Wierzbicki, 1977; Wierzbicki, 1986; Miettinen, 1999, p. 30).

An important property of ϵ-properly Pareto optimal solutions is that tradeoffs between them are bounded by ϵ and $1/\epsilon$ (Wierzbicki, 1986). The set of ϵ-properly Pareto optimal solutions is the smallest set of the three types of Pareto optimal sets defined here. It can be extended to become the Pareto optimal set by allowing unbounded tradeoffs. The Pareto optimal set can be further extended to become the weakly Pareto optimal set by allowing deterioration of an objective value without any change in the other objective values. Figure 2.3 shows the relationship between the weakly Pareto optimal set and the Pareto optimal set. Figure 2.4 illustrates the ϵ-properly Pareto optimal set and how it relates to the Pareto optimal set.

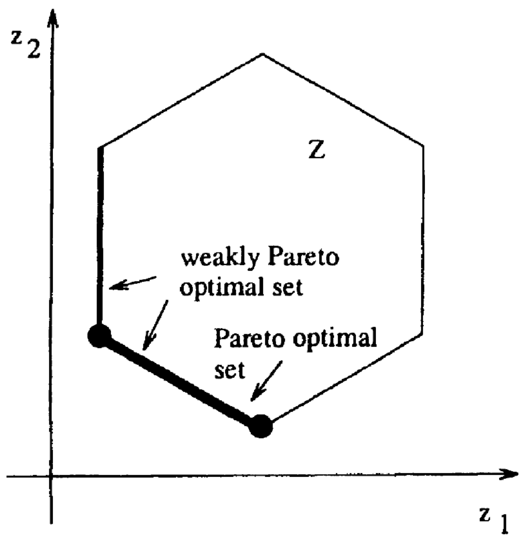

Figure 2.3: Illustration by Miettinen (1999, p. 20), showing a feasible objective region Z and the weakly Pareto optimal set with its subset, the Pareto optimal set.

It follows from the definition of Pareto optimality that moving from one Pareto optimal solution to the next requires a tradeoff. This is one of the defining characteristics of multiobjective optimization. To determine the best tradeoffs between conflicting objectives, a pure mathematical analysis is not sufficient. Finding a set of Pareto optimal solutions is as close as we get to a final solution of our original Problem (2.2) with the given information. To go further, we need help from a decision maker (DM). A decision maker is someone who knows the problem area well and is usually responsible for the final solution (Miettinen, 1999, p.14). The DM can give valuable information about their preferences to guide the solution process. They can, for example, determine desirable or acceptable levels of the objective function values. These

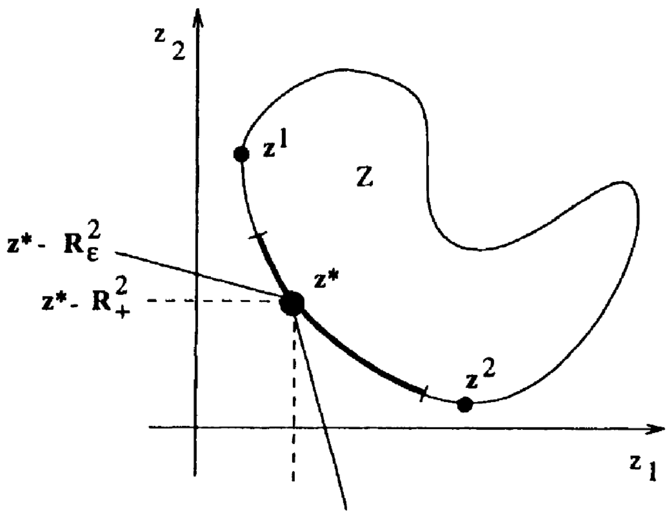

Figure 2.4: Illustration by Miettinen (1999, p. 31), depicting a feasible objective region Z and the set of ϵ-properly Pareto optimal solutions as the bold line. The end points of the Pareto optimal set are marked with $\boldsymbol{z}^1$ and $\boldsymbol{z}^2$ for comparison. $\boldsymbol{z}^*$ is one example of an ϵ-properly Pareto optimal solution at the tip of the blunt cone introduced in the definition (see Definition 2.3.3).

are called aspiration levels and denoted by $\bar{z}_i, i = 1, ..., k$ (Miettinen, 1999, p.14). The vector $\bar{\boldsymbol{z}} \in \mathbb{R}^k$, consisting of aspiration levels, is called a reference point.

Because the Pareto optimal set is so important when solving a multiobjective optimization problem, it is often useful to consider the boundaries of this set. We begin at the lower bound. We define an ideal objective vector as an objective vector that minimizes each of the objective functions (Miettinen, 1999, p.15).

Definition 2.3.4. The components $z_i^\star$ of the ideal objective vector $\boldsymbol{z}^\star \in \mathbb{R}^k$ are obtained by minimizing each of the objective functions individually subject to constraints, i.e., by solving

$$\begin{array}{ll} \text{minimize} & f_i(\boldsymbol{x}) \\ \text{subject to} & \boldsymbol{x} \in S \end{array}$$

for $i = 1, ..., k$ (Miettinen, 1999, p.16).

If the ideal objective vector would lie in the feasible objective region, that is, if $\boldsymbol{z}^\star \in Z$, it would be the only Pareto optimal solution. In general, however, our objectives are always conflicting, and the ideal objective vector is infeasible as a result. Even though it can never be reached, it is a useful concept. For example, the decision maker may want to set their reference point to the ideal objective vector or use it to guide their goal-setting. A utopian objective vector $\boldsymbol{z}^{\star\star} \in \mathbb{R}^k$ is even more unreachable than the ideal objective vector. It is an infeasible objective vector whose components are formed by

$$z_i^{\star\star} = z_i^{\star} - \epsilon_i$$

for all $i = 1, ..., k$, where $z_i^{\star}$ is a component of the ideal objective vector and $\epsilon_i > 0$ is a relatively small but computationally significant scalar (Miettinen, 1999, p.16).

The ideal and utopian objective vectors together give sufficient means to meaningfully express the lower bounds of the components of the Pareto optimal objective vectors. The upper bounds are a bit trickier. For those, we define the nadir objective vector using the definition by Ehrgott (2005, p.34) with the notation from Miettinen (1999).

Definition 2.3.5. A nadir objective vector $\boldsymbol{z}^{\mathrm{nad}} \in \mathbb{R}^k$ is an objective vector whose components z_i^{nad} are obtained by solving

$$\begin{aligned} &\text{maximize} && f_i(\boldsymbol{x}) \\ &\text{subject to} && \boldsymbol{x} \in S_P \end{aligned}$$

for all $i = 1, ..., k$, where S_P is the set of Pareto optimal decision vectors.

Figure 2.5 has a visual representation of the ideal and nadir objective vectors on a given feasible objective region $Z \subset \mathbb{R}^2$. We can clearly see how the ideal objective vector is feasible only in the most trivial case, but the nadir objective vector may be feasible or infeasible depending purely on the shape of the feasible objective region. The components of the nadir objective vector are much more difficult to obtain compared to the ideal objective vector, because optimization over the set of Pareto optimal decision vectors is required (Ehrgott, 2005, p. 34). Miettinen (1999, p.16) describes a method for estimating the nadir objective vector with a payoff table. A payoff table, shown in Table 2.1, is formed by first finding the ideal objective vector. We denote with $\boldsymbol{x}^i$ the decision variable vector that minimizes the objective function f_i. Row i of the payoff table is formed by evaluating each objective function in point $\boldsymbol{x}^i$. Now the main diagonal of the table forms the ideal objective vector $\boldsymbol{z}^{\star}$. An estimate for the nadir objective vector $\tilde{\boldsymbol{z}}^{\mathrm{nad}}$ is formed by the maximal values of each column, that is

$$\tilde{z}_i^{\mathrm{nad}} = \max_{j=1,...,k} f_i(\boldsymbol{x}^j).$$

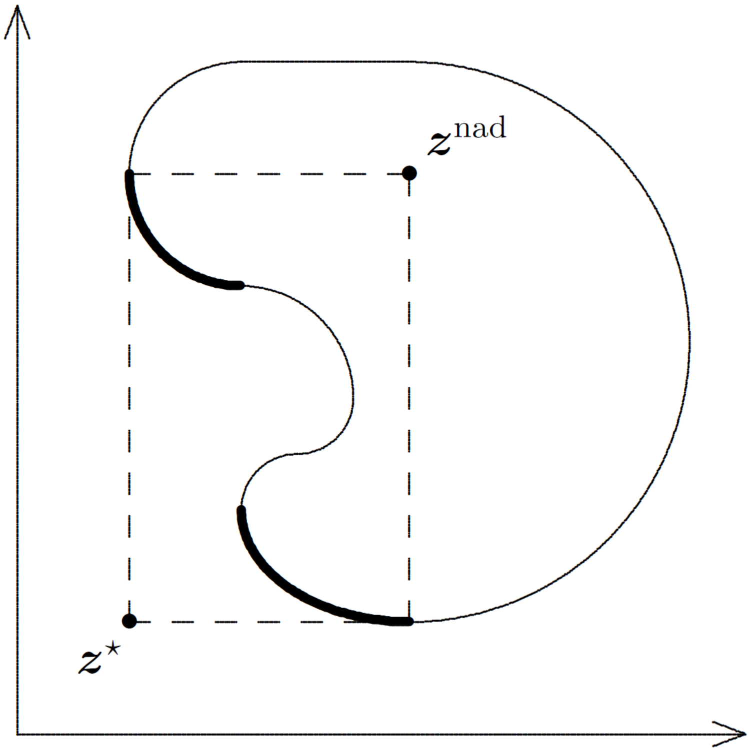

Figure 2.5: Illustration based on an image by Ehrgott (2005, p.35), showing a feasible objective region $Z \subset \mathbb{R}^2$, the Pareto optimal set as the thick line, the ideal objective vector $\boldsymbol{z}^{\star}$ and the nadir objective vector $\boldsymbol{z}^{\mathrm{nad}}$.

The accuracy of the estimate depends on the shape of the feasible objective region. The components $\tilde{z}_i^{\mathrm{nad}}$ of the estimate may be lower or higher than the real values z_i^{nad}, when there are more than two objective functions, and when a single objective function has multiple optimal solutions (Ehrgott, 2005, p.35). Weistroffer (1985) has demonstrated some situations where estimates based on a payoff table do not equal the real values. For a general multiobjective optimization problem, there is no constructive method for calculating the nadir objective vector (Miettinen, 1999, p.17). Despite the limitations of the payoff table approach, it can be used to form a useful estimate as long as its robustness is kept in mind.

Many of the methods utilize scalarization in some shape or form. Scalarization means that the multiobjective optimization problem is converted into a single objective problem by constructing a real-valued (scalar) objective function (Miettinen, 1999, p.4). It is often useful to categorize objective functions based on how their values increase. Next, we define increasing,

Table 2.1: Payoff table

$f_1(\boldsymbol{x}^1)$	$f_2(\boldsymbol{x}^1)$	$\dots$	$f_i(\boldsymbol{x}^1)$	$\dots$	$f_k(\boldsymbol{x}^1)$
$f_1(\boldsymbol{x}^2)$	$f_2(\boldsymbol{x}^2)$	$\dots$	$f_i(\boldsymbol{x}^2)$	$\dots$	$f_k(\boldsymbol{x}^2)$
$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
$f_1(\boldsymbol{x}^i)$	$f_2(\boldsymbol{x}^i)$	$\dots$	$f_i(\boldsymbol{x}^i)$	$\dots$	$f_k(\boldsymbol{x}^i)$
$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
$f_1(\boldsymbol{x}^k)$	$f_2(\boldsymbol{x}^k)$	$\dots$	$f_i(\boldsymbol{x}^k)$	$\dots$	$f_k(\boldsymbol{x}^k)$

strictly increasing, strongly increasing and ϵ-strongly increasing functions.

Definition 2.3.6. (Miettinen, 1999, pp. 8–9). Assume $\boldsymbol{x}^1, \boldsymbol{x}^2 \in \mathbb{R}^n$. A function $f_i : \mathbb{R}^n \to \mathbb{R}$ is

i) increasing if

$$x_j^1 \leq x_j^2 \text{ for all } j = 1, ..., n \text{ implies } f_i(\boldsymbol{x}^1) \leq f_i(\boldsymbol{x}^2),$$

ii) strictly increasing if

$$x_j^1 < x_j^2 \text{ for all } j = 1, ..., n \text{ implies } f_i(\boldsymbol{x}^1) < f_i(\boldsymbol{x}^2),$$

iii) strongly increasing if

$$x_j^1 \leq x_j^2 \text{ for all } j = 1, ..., n \text{ and } x_l^1 < x_l^2 \text{ for some } l \text{ implies}$$
$$f_i(\boldsymbol{x}^1) < f_i(\boldsymbol{x}^2),$$

iv) ϵ-strongly increasing if

$$\boldsymbol{x}^1 \in \boldsymbol{x}^2 - \mathbb{R}_\epsilon^n \setminus \{\boldsymbol{0}\} \text{ implies } f_i(\boldsymbol{x}^1) < f_i(\boldsymbol{x}^2),$$

where $\mathbb{R}_\epsilon^n = \{\boldsymbol{x} \in \mathbb{R}^n | \operatorname{dist}(\boldsymbol{x}, \mathbb{R}_+^n) \leq \epsilon \|\boldsymbol{x}\|\}$ is a blunt cone and $\epsilon > 0$ is a predetermined scalar.

2.3.2 Achievement scalarizing function approach

The idea of achievement scalarizing functions was introduced by Wierzbicki (1982). This method is based on a reference point $\bar{\boldsymbol{z}} \in \mathbb{R}^k$. The central idea is to project the reference point onto the set of Pareto optimal solutions (Branke et al., 2008). The projection changes when the reference point is moved, so different Pareto optimal solutions can be produced. We denote an achievement scalarizing function as $s_{\bar{\boldsymbol{z}}}(\boldsymbol{z}) : Z \to \mathbb{R}$. Next, we define order-representing and order-approximating achievement scalarizing functions by building on the concepts of strictly, strongly, and ϵ-strongly increasing functions introduced in Definition 2.3.6.

Definition 2.3.7. A continuous achievement scalarizing function $s_{\bar{\boldsymbol{z}}}(\boldsymbol{z}) : Z \to \mathbb{R}$ is order-representing if it is strictly increasing as a function of $\boldsymbol{z} \in Z$ for any $\bar{\boldsymbol{z}} \in \mathbb{R}^k$ and if

$$\{\boldsymbol{z} \in \mathbb{R}^k \mid s_{\bar{\boldsymbol{z}}}(\boldsymbol{z}) < 0\} = \bar{\boldsymbol{z}} - \operatorname{int} \mathbb{R}^k_+$$

for all $\bar{\boldsymbol{z}} \in \mathbb{R}^k$ (Miettinen, 1999, p.108).

Definition 2.3.8. A continuous achievement scalarizing function $s_{\bar{\boldsymbol{z}}}(\boldsymbol{z}) : Z \to \mathbb{R}$ is order-approximating if it is strongly increasing as a function of $\boldsymbol{z} \in Z$ for any $\bar{\boldsymbol{z}} \in \mathbb{R}^k$ and if

$$\bar{\boldsymbol{z}} - \mathbb{R}^k_{\bar{\epsilon}} \subset \{\boldsymbol{z} \in \mathbb{R}^k \mid s_{\bar{\boldsymbol{z}}}(\boldsymbol{z}) \leq 0\} \subset \bar{\boldsymbol{z}} - \mathbb{R}^k_{\epsilon}$$

for all $\bar{\boldsymbol{z}} \in \mathbb{R}^k$ and with $\epsilon > \bar{\epsilon} \geq 0$ (Miettinen, 1999, p.108).

With the above definitions we are now ready to present a theorem relating these two classes of achievement scalarizing functions to concepts of Pareto optimality, as presented in Miettinen (1999, p.109). The problem we are solving is

$$\begin{aligned} &\text{minimize} && s_{\bar{\boldsymbol{z}}}(\boldsymbol{z}) \\ &\text{subject to} && \boldsymbol{z} \in Z. \end{aligned} \tag{2.3}$$

Theorem 2.3.1. *If the achievement scalarizing function $s_{\bar{\boldsymbol{z}}}(\boldsymbol{z}) : Z \to \mathbb{R}$ is order-representing, then, for any $\bar{\boldsymbol{z}} \in \mathbb{R}^k$, the solution of Problem (2.3) is weakly Pareto optimal. If the achievement scalarizing function $s_{\bar{\boldsymbol{z}}}(\boldsymbol{z}) : Z \to \mathbb{R}$ is order-approximating with some ϵ and $\bar{\epsilon}$ as in Definition 2.3.8, then, for any $\bar{\boldsymbol{z}} \in \mathbb{R}^k$, the solution of Problem (2.3) is Pareto optimal. If in addition $s_{\bar{\boldsymbol{z}}}$ is $\bar{\epsilon}$-strongly increasing, then the solution of Problem (2.3) is $\bar{\epsilon}$-properly Pareto optimal.*

Proof. See Miettinen (1999, p.109).

The above theorem gives us the sufficient conditions for a solution of Problem (2.3) to be weakly Pareto optimal, Pareto optimal or ϵ-properly Pareto optimal. It is also possible to prove the corresponding necessary conditions. This gives us the following theorem with the form presented by Miettinen (1999, p.110).

Theorem 2.3.2. *If the achievement scalarizing function* $s_{\bar{z}}(\boldsymbol{z}) : Z \to \mathbb{R}$ *is order-representing and* $\boldsymbol{z}^* \in Z$ *is weakly Pareto optimal or Pareto optimal, then it is a solution of Problem (2.3) with* $\bar{\boldsymbol{z}} = \boldsymbol{z}^*$ *and the value of the achievement scalarizing function is zero. If the achievement scalarizing function* $s_{\bar{z}}(\boldsymbol{z}) : Z \to \mathbb{R}$ *is order-approximating and* $\boldsymbol{z}^* \in Z$ *is* ϵ*-properly Pareto optimal, then it is a solution of Problem (2.3) with* $\bar{\boldsymbol{z}} = \boldsymbol{z}^*$ *and the value of the achievement scalarizing function is zero.*

Proof. See Wierzbicki (1986).

We are now able to completely characterize the set of weakly Pareto optimal solutions, and, with the additional assumption of uniqueness of solutions to Problem (2.3), also the set of Pareto optimal solutions (Miettinen, 1999, p.110). We move to consider what happens when a feasible or infeasible reference point is chosen. To be more exact, we consider the difference between the situations where the reference point is in the feasible set or in a cone in the nonnegative direction from the feasible set $\bar{\boldsymbol{z}} \in Z + \mathbb{R}^k_+$ and its complement $\bar{\boldsymbol{z}} \notin Z + \mathbb{R}^k_+$. If $\bar{\boldsymbol{z}} \in Z + \mathbb{R}^k_+$, minimizing the achievement scalarizing function subject to the feasible region produces a Pareto optimal solution by allocating slack between the reference point and the Pareto optimal set. If $\bar{\boldsymbol{z}} \notin Z + \mathbb{R}^k_+$, the minimization produces a Pareto optimal solution by minimizing the distance between the reference point and the feasible set. In both cases, we reach a solution that is a projection of the reference point on the Pareto optimal set. The behavior is the same no matter which achievement scalarizing function formulation is chosen (Branke et al., 2008, p.18). Achievement scalarizing functions have the advantage that any weakly Pareto optimal or Pareto optimal solution can be reached by moving the reference point (Miettinen, 1999, p.111). Wierzbicki (1982) shows also that the solution to the problem of minimizing an achievement scalarizing function depends Lipschitz-continuously on the reference point. This means that the method has local controllability. If the decision maker moves the reference point slightly, it does not cause drastic and unexpected changes in the solution.

There are many ways to formulate suitable achievement scalarizing functions. A prevalent example is the function

$$s_{\bar{z}}(\boldsymbol{z}) = \max_{i=1,\dots,k}[w_i(z_i - \bar{z}_i)] + \rho \sum_{i=1}^{k} w_i(z_i - \bar{z}_i), \tag{2.4}$$

where $\boldsymbol{w}$ is a fixed normalizing vector, for example $w_i = 1/(z_i^{nad} - z_i^{\star\star})$ for all i, and $\rho > 0$ is an augmentation multiplier that is sufficiently small when compared to ϵ and large when compared to $\bar{\epsilon}$. This function is very useful because it is both order-approximating and $\bar{\epsilon}$-strongly increasing (Wierzbicki, 1986; Miettinen, 1999, p.111). Thus, on the basis of Theorem 2.3.1, we can guarantee that with it solutions of Problem (2.3) are $\bar{\epsilon}$-properly Pareto optimal.

Chapter 3

Call allocation model

This chapter details the optimization model that is implemented in this thesis. We begin in Section 3.1 by formulating our optimization task and then move on to finding suitable values for the different parameters that go into it. In Section 3.2, we discuss modifications that are required when nadir and utopian values are unavailable.

3.1 Optimization task formulation

As shown in Section 2.3.2, the achievement scalarizing function method has useful properties for this case. With this method, all Pareto optimal solutions can be reached, and the solution changes continuously with changes in preferences. We can formulate our optimization task with an achievement scalarizing function given in Equation (2.4) as

$$\begin{aligned}
\text{minimize} \quad & \max\left[w_E\left(E(\boldsymbol{x})-\bar{E}\right),\;\; w_T\left(T(\boldsymbol{x})-\bar{T}\right),\;\; w_W\left(W(\boldsymbol{x})-\overline{W}\right)\right] \\
& + \rho\left[w_E\left(E(\boldsymbol{x})-\bar{E}\right)+w_T\left(T(\boldsymbol{x})-\bar{T}\right)+w_W\left(W(\boldsymbol{x})-\overline{W}\right)\right] \\
\text{subject to} \quad & \boldsymbol{x}\in S
\end{aligned}$$

with the following notation:

$\boldsymbol{x}$	Allocation of calls
S	Set of feasible call allocations
ρ	Small augmentation multiplier
$E(\boldsymbol{x})$	Energy consumption objective function
$T(\boldsymbol{x})$	Time to destination objective function
$W(\boldsymbol{x})$	Waiting time objective function
$\bar{E}, \bar{T}, \overline{W}$	Aspiration levels
w_E, w_T, w_W	Normalizing factors

This single objective problem is solved with the same genetic algorithm already in use in the existing group controller (Tyni & Ylinen, 2001). The group controller generates the set of feasible call allocations S. There are many situations when an arbitrary call cannot be allocated to any of the cars in the elevator group. For example, one of the cars may be out of order, some floors may be restricted to some cars due to security reasons, or mixing of some passenger groups is not allowed. If an allocation of calls $\boldsymbol{x}$ would contain such an allocation that a car could not answer a call given to it, the allocation would be infeasible. These infeasible solutions are not included in S.

Figure 3.1 illustrates two feasible call allocations. According to the general preference statements introduced in Section 2.2.2, both of these alternatives could be preferable. Their preference order depends on traffic intensity. In high traffic, it would be desirable to dispatch all three elevator cars to serve the three passengers individually, because this minimizes time to destination. In low traffic, it would be desirable to dispatch only one elevator car to serve all three passengers, because this would reduce energy consumption significantly with only a modest increase in waiting time. Information about time to destination and waiting time associated with each feasible allocation is available to the call allocation system, but an energy consumption metric

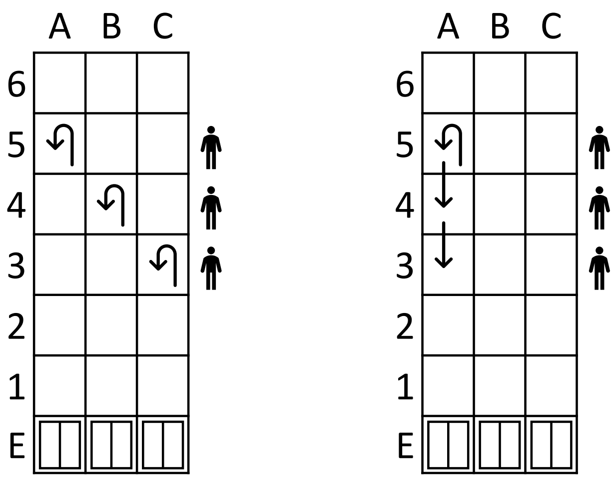

Figure 3.1: Desirable call allocations when focusing on reducing time to destination (left) and energy consumption (right) in a situation where three passengers are heading for the entrance floor and all elevator cars start there.

is currently not included in the group controller. For the purposes of this thesis, energy consumption is estimated with the total distance the cars must travel in each allocation. The use of this estimate should lead to a desirable outcome as energy is saved by minimizing car movement. Tyni and Ylinen (2006) discussed a more elaborate model for estimating energy consumption that could be tested as a next step in development after the current study.

The purpose of the normalizing factors w_i is to scale the different objective values so that their changes are comparable to one another. The normalizing factors can be constructed with the nadir and utopian values, defined in Section 2.3.1, as follows:

$$\begin{aligned} w_E &= \frac{1}{E^{\text{nad}} - E^{\star\star}} \\ w_T &= \frac{1}{T^{\text{nad}} - T^{\star\star}} \\ w_W &= \frac{1}{W^{\text{nad}} - W^{\star\star}}. \end{aligned}$$

The augmentation multiplier ρ can be used to limit the tradeoffs the call allocation system is allowed to make. By setting $\rho = 0$, the tradeoffs are unbounded. This may lead to unstable behavior and spikes in the objective values without noticeable improvement in others. A small positive value $\rho = 0.05$ is tested here to prohibit completely unbounded tradeoffs. This can be later adjusted based on possible feedback of the results of this study.

Choosing the aspiration levels for each objective is an important task. As discussed in Section 2.2.2, ideally there would be some simple parameters that can be used to adjust the call allocation behavior. Let us, instead of assigning values to the aspiration levels directly, consider three parameters, $\lambda_E, \lambda_T, \lambda_W \in [0, 1]$, to simplify preference adjustment. They signify, respectively, the importance of minimizing energy consumption, time to destination, and waiting time. Let us further define $\lambda_E + \lambda_T + \lambda_W = 1$ to make the parameter values illustrate clearly where the focus of the optimization is. Without this condition, we could have a situation where we can set all three values to zero and it would capture the same preferences as setting them to one. According to the preference statements introduced in Section 2.2.2, in high traffic we should focus on minimizing time to destination and set $\lambda_E = 0, \lambda_T = 1$, and $\lambda_W = 0$. In low traffic we will focus on minimizing energy consumption while keeping waiting times at a reasonable level by setting e.g. $\lambda_E = 0.7, \lambda_T = 0$, and $\lambda_W = 0.3$. Between these two extremes, there should be some simple mechanism for tuning the parameters based on traffic intensity.

Let us denote traffic intensity with I. When $I = 0$, there is no traffic at all. When $I = 1$, the traffic is at a level where the elevator group is at its maximum handling capacity. When $I > 1$, there is more traffic than the elevator group can handle, and queues start to form. The simplest conceivable method for tuning the parameters λ_i would be to define some threshold, e.g. $I = 0.8$, and set the parameters as in low traffic before that and as in high traffic after. Such a sudden change seems risky, so a better alternative would be some curve that would shift a parameter continuously between the two extremes. When $I < 0.6$, we can be confident that the elevator system can handle the incoming traffic without gathering queues. After that we should start putting more and more focus on optimizing time to destination instead of energy consumption and waiting time. After a smooth transition period, at $I = 1$, all efforts should be put in optimizing time to destination to handle the incoming traffic without queues. The curve

$$\frac{1}{1 + e^{-x}}$$

has a suitable shape for this adjustment purpose. It is called a logistic curve, and it is plotted in Figure 3.2. It fulfills our requirements of smoothly moving a value between two extremes during a finite transition period. This general shape can now be used to define the parameters λ_i as a function of I with the extremes discussed above and a transition period at $0.6 < I < 1$. By transforming the formula to match these specifications, we can define

$$\begin{aligned}
\lambda_E(I) &= 0.7 - \frac{0.7}{1 + e^{-20(I-0.8)}} \\
\lambda_T(I) &= \frac{1}{1 + e^{-20(I-0.8)}} \\
\lambda_W(I) &= 1 - \lambda_E(I) - \lambda_T(I)
\end{aligned}$$

to achieve the smooth and continuous parameter tuning shown in Figure 3.3. These definitions are by no means the only ones that can be considered to reflect the desired call allocation behavior. As such, they should be seen as a starting point rather than a definitive best practice for tuning the parameters.

Using the newly constructed functions $\lambda_i(I)$, the aspiration levels for each objective can be set in relation to the Pareto front. With the help of the nadir and utopian values, we define the aspiration levels as

$$\begin{aligned}
\bar{E} &= (1 - \lambda_E)E^{\text{nad}} + \lambda_E E^{\star\star} \\
\bar{T} &= (1 - \lambda_T)T^{\text{nad}} + \lambda_T T^{\star\star} \\
\bar{W} &= (1 - \lambda_W)W^{\text{nad}} + \lambda_W W^{\star\star}.
\end{aligned}$$

This gives a more concrete meaning to the parameters λ_i. A given λ_i can now be interpreted as the relative position of an aspiration level between the

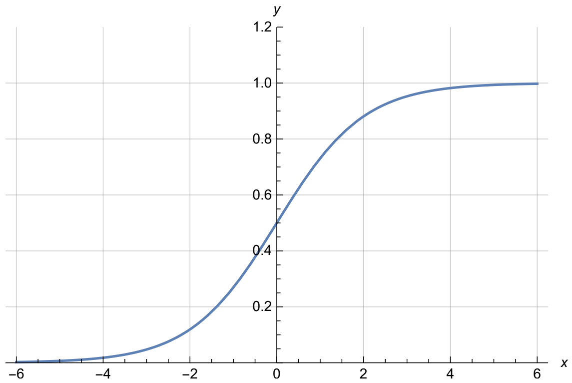

Figure 3.2: An example of a suitable curve for tuning the parameters λ_i.

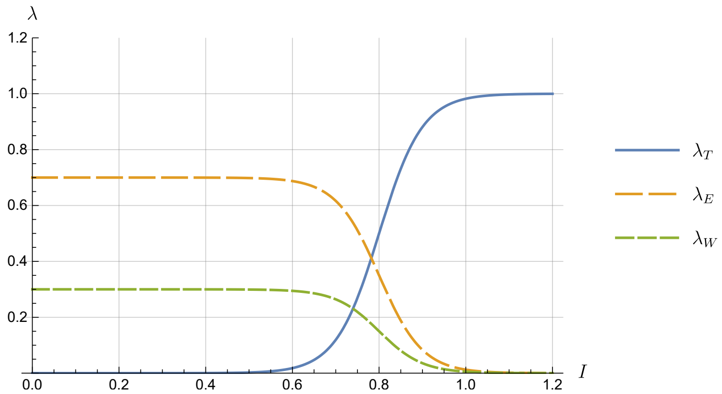

Figure 3.3: Tuning of the parameters λ_i as functions of traffic intensity I.

nadir and utopian levels of an objective function. $\lambda_i = 1$ means that the aspiration level is the utopian level, and $\lambda_i = 0$ means that the aspiration level is the nadir level. Different functions $\lambda_i(I)$ should be tested to reach the most desirable behavior of the group control system over multiple allocations. However, for the purposes of the current study, it is sufficient that we have found a tuning of aspiration levels that can be said to fulfill the general preference statements given in Section 2.2.2. When traffic is high, we try to reach the utopian level of time to destination, even if that would mean the other objectives reach their nadir levels. When traffic is low, we try to find a balanced solution close to the utopian level of energy consumption, while not compromising too much on waiting time, and allowing time to destination to increase as high as its nadir level if necessary.

3.2 Formulation without nadir and utopian values

As discussed in Section 2.3.1, finding the components of the nadir objective vector is difficult. The introduced payoff table approach provides a useful estimation method, but its accuracy is highly dependent on the shape of the feasible objective region. Finding the utopian objective vector is much easier, but it also requires some information about the feasible objective region. Because of these estimation difficulties, it is not always possible to have nadir and utopian values for the formulation. This is the situation also in the current study where finding the utopian and nadir values before optimization proved to be an unattractive alternative due to computational limitations. This section adjusts the formulation for the situation where utopian and nadir values are unavailable.

Tyni and Ylinen (2006) introduced a viable technique to overcome these difficulties by using the sample mean and the sample standard deviation (Ross, 2014, pp. 208–219) of the generated solution candidates. The initial step of the genetic algorithm used at KONE involves generating 50 feasible solutions at random. This random sample can be used to calculate the sample means m_i and sample standard deviations s_i as

$$m_i = \frac{1}{N}\sum_{j=1}^{N} f_{i,j}$$

$$s_i = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}(f_{i,j} - m_i)^2},$$

where f_i are the three objective functions E, T, and W, $N = 50$ is the sample size, and j is the index of a solution candidate. Now we can use the sample standard deviation to normalize the objectives instead of the nadir and utopian values. We define the normalizing factors w_i as

$$w_i = \frac{1}{s_i}.$$

The nadir and utopian values would also be useful in reference point adjustment. In their absence we have to set the reference point in relation to the whole feasible objective region instead of the Pareto front. This is much less accurate as we have no a priori knowledge of the shape of the feasible objective region or its relation to the Pareto front. We can estimate the boundaries of the feasible objective with the sample means and sample standard deviations of the objectives. Here we will use two standard deviations to estimate the distance of the boundary from the mean, i.e. $m_i \pm s_i$. Setting the reference point in relation to the feasible objective region is quite crude, and there is a possibility for some of the aspiration levels to miss the Pareto front entirely. This would lead to optimization where one of the objectives has almost no effect even if an effect was intended. The lower boundary is the most reliable anchor point because we can be relatively confident that it is close to the utopian level of an objective. Increasing the aspiration level from that comes with a rising risk of moving past the nadir level and an untimely loss of relevance in the optimization as a result. This effect can be visualized with the help of Figure 2.5 in Section 2.3.1.

To avoid this risk, we will set both energy consumption and waiting time aspiration levels to the lower boundary when traffic is low, instead of putting more focus on reducing energy consumption. Now only the parameter λ_T is needed in addition to the sample means and sample standard deviations to redefine the aspiration levels as

$$\begin{aligned}\bar{T} &= (1-\lambda_T)(m_T + 2s_T) + \lambda_T(m_T - 2s_T)\\ \bar{E} &= \lambda_T(m_E + 2s_E) + (1-\lambda_T)(m_E - 2s_E)\\ \overline{W} &= \lambda_T(m_W + 2s_W) + (1-\lambda_T)(m_W - 2s_W).\end{aligned}$$

The above sets the aspiration level for time to destination to its estimated upper bound $m_T + 2s_T$ in low traffic, and to its estimated lower bound $m_T - 2s_T$ in high traffic. The opposite happens to the aspiration levels of energy consumption and waiting time. The reference point moves along a line through the feasible objective region, with endpoints at $\bar{\boldsymbol{z}}_{\text{low}} = (\bar{E}_{\text{low}}, \bar{T}_{\text{low}}, \overline{W}_{\text{low}}) = (m_E - 2s_E, m_T + 2s_T, m_W - 2s_W)$ and $\bar{\boldsymbol{z}}_{\text{high}} = (m_E + 2s_E, m_T - 2s_T, m_W + 2s_W)$. We can visualize this by modifying Figure 2.5 to show the possible reference points. Figure 3.4 now shows an example projection of the feasible objective region onto the TE-plane. The reference point moves along the solid line between the two extremes based on traffic intensity. As discussed in Section 2.3.2, the achievement scalarizing function finds the solution by projecting the reference point onto the Pareto optimal set. Even though it is easy to compose an example image, we should keep in mind that we do not have a priori knowledge of the shape or the boundaries of the feasible objective region, so the reference point has to be set based on estimated boundaries.

To illustrate the effect of the normalizing factor together with the aspiration level adjustment, we can plug these into the achievement scalarizing function.

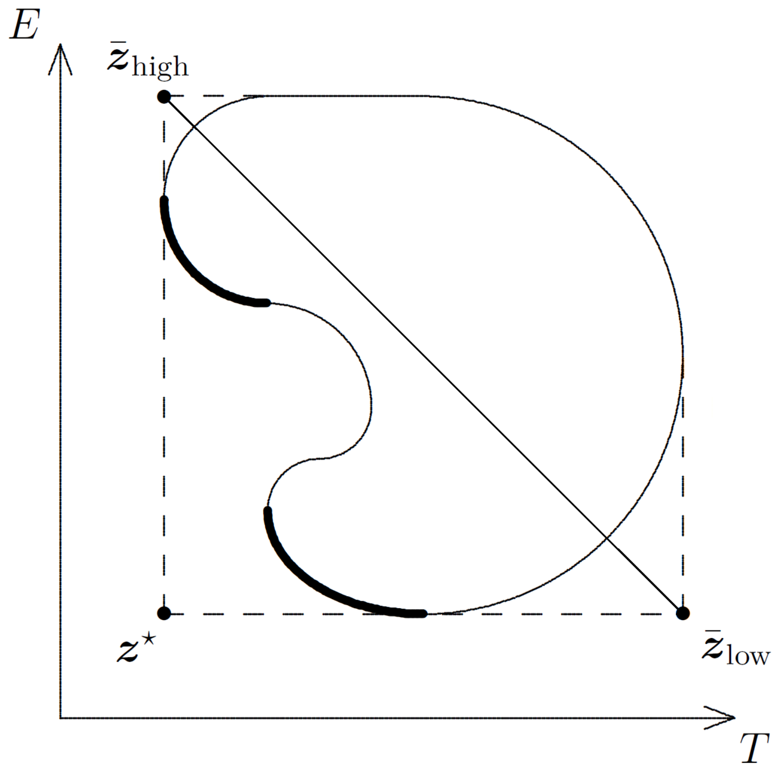

Figure 3.4: Example projection of the feasible objective region onto the TE-plane, with the Pareto optimal set as the thick line, the ideal objective vector $\boldsymbol{z}^{\star}$, and the reference point in high traffic $\bar{\boldsymbol{z}}_{\text{high}}$ and in low traffic $\bar{\boldsymbol{z}}_{\text{low}}$. The reference point moves between the two extremes along the solid line based on traffic intensity. This illustration is based on an image by Ehrgott (2005, p.35).

Because of symmetry, the effect is visible by considering e.g. the first term

$$\begin{aligned}
&w_E\left(E(\boldsymbol{x}) - \overline{E}\right) \\
=&\frac{1}{s_E}\left[E(\boldsymbol{x}) - (\lambda_T(m_E + 2s_E) + (1-\lambda_T)(m_E - 2s_E))\right] \\
=&\frac{E(\boldsymbol{x}) - m_E}{s_E} + 2 - 4\lambda_T.
\end{aligned}$$

This form can be interpreted as first scaling the energy consumption with its sample mean and sample standard deviation, and then moving the scaled objective value by two units in either direction. One unit in the scaled objective value corresponds to one standard deviation which connects this form to the estimated bounds.

Chapter 4

Simulation results

In this chapter, the call allocation system developed in this thesis is tested in a simulation environment. Section 4.1 introduces the simulation environment, along with the building, elevator group, and traffic models used in the simulations. Section 4.2 provides a performance analysis. In Section 4.3, we attempt to replicate the behavior of the unmodified group controller to validate the functionality of the new system. In Section 4.4, we analyze the sensitivity of the new system to changes in reference point adjustment. Section 4.5 begins with a brief summary of the results from all simulations. We then move to discuss the findings and the directions for further development that these results give.

4.1 Simulation setup

Since its development, KONE Building Traffic Simulator (BTS) (Siikonen et al., 2001) has become a standard tool for testing the quality of new features in KONE group control systems. In addition to detailed simulations, it provides the user with a host of statistical information about the performance of the system. Even though energy consumption information is not directly available to the call allocation system, BTS calculates it during the simulation along with time to destination and waiting time statistics.

To evaluate the usefulness of the modifications developed in this thesis, simulations with three different elevator group models are used. These three models were chosen because they represent common elevator groups in typical buildings. As such, they serve well in initial testing of the modified call allocation system. They include a small 2-elevator group in a 9-storey office building, a 4-elevator group in a 13-storey office building, and a larger 8-elevator group in a 21-storey office building. All entrances in these buildings are in a non-populated entrance floor at street level. The occupied floors above the entrance floor are evenly populated. The properties of the three models are detailed in Table 4.1.

To get a good overview of the behavior of the new call allocation system across many different traffic situations, the traffic of a full working day is simulated. The daily traffic profile used in the simulations is illustrated in Figure 4.1. Typical traffic conditions introduced in Section 2.1 are clearly visible. There is a morning up peak, a discernible lunchtime traffic condition, and a down peak at the end of the working day.

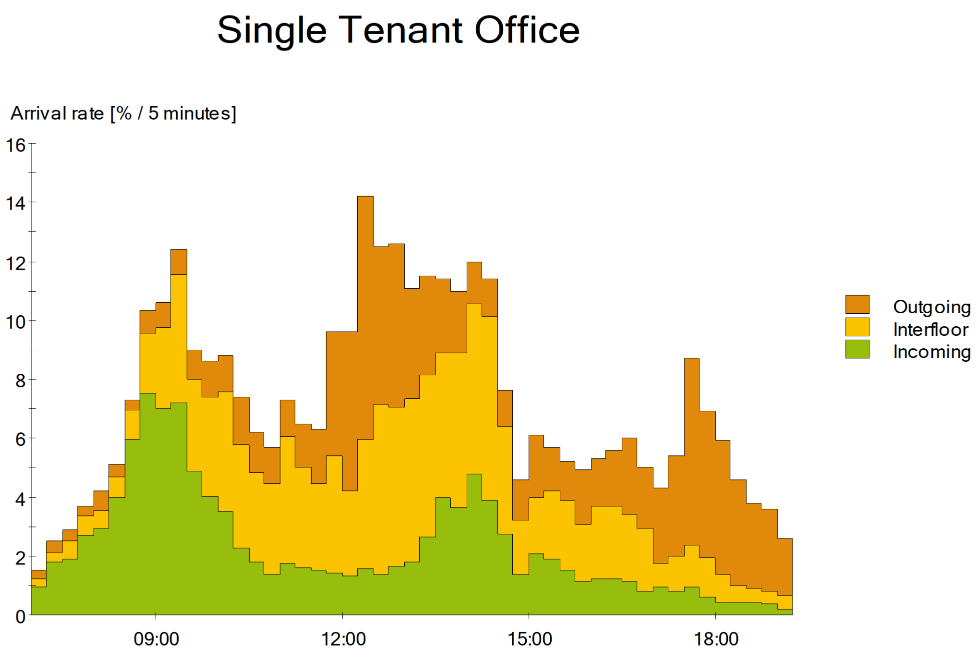

Figure 4.1: The daily traffic profile used in the simulations. The arrival rate of passengers in a 5-minute period is given as a percentage of the total population of the building.

Table 4.1: Parameters of the three elevator group models used in simulations. The last six parameters are the same in all simulated elevators.

Number of elevators	2	4	8
Occupied floors	1-8	1-12	1-20
Population per occupied floor	50	65	92
Top floor level [m]	32	48	80
Rated carload [persons]	10	13	24
Bypass load [persons]	8	10	19
Rated speed [m/s]	1.6	2	3.5
Acceleration [m/s2]	0.8	0.8	1
Jerk [m/s3]	1.2	1.2	1.6
Door width [mm]	900	1100	1200
Door closing time [s]	2.7	3.1	3.4
Door opening time [s]	1.4	1.4	1.4
Transfer times per passenger [s]	2.2	2	1.9
Photocell delay [s]	0.9	0.9	0.9
Start delay [s]	0.7	0.7	0.7
Floor height [m]	4	4	4
Advance door opening distance [m]	0.15	0.15	0.15
Advance door opening speed [m/s]	0.3	0.3	0.3
Door opening	center	center	center
Control type	DCS	DCS	DCS

4.2 Performance analysis

To analyze the performance of the new call allocation system, daily traffic is simulated in all three elevator group models with and without the modifications developed in this thesis. This creates a total of six simulation runs. The simulation results from each elevator group are introduced in separate sections, and points of interest are highlighted.

4.2.1 2-elevator group

Changing the group control had little effect in the 2-elevator group. Figure 4.2 shows the energy consumption time series for this group. The curves of the experimental and the production group control follow one another very closely, and there are no major differences that would stand out from the noise. Energy consumption for the whole day was reduced by 4%. The results for time to destination (Figure 4.3) and waiting time (Figure 4.4) tell a similar story of slight change, if any. Overall, both time to destination and waiting time increased by 5%.

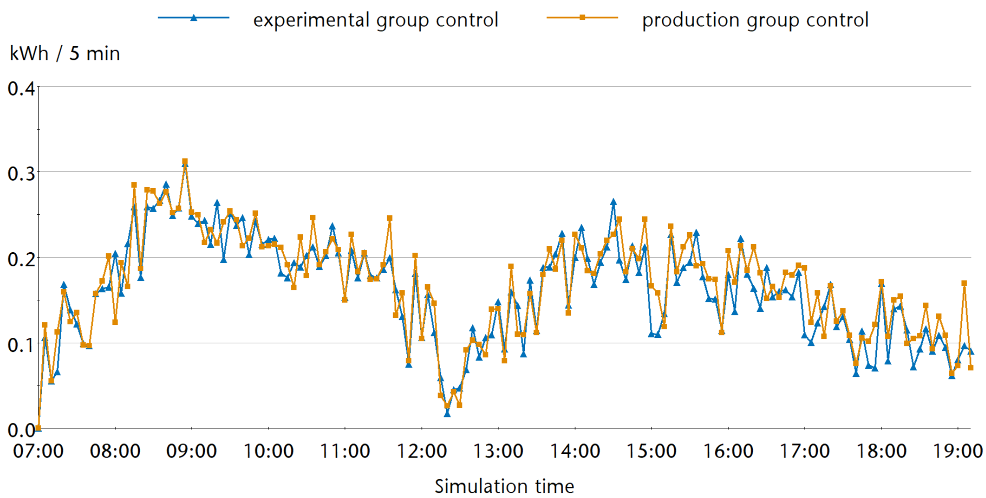

Figure 4.2: Energy consumption in 2-elevator group.

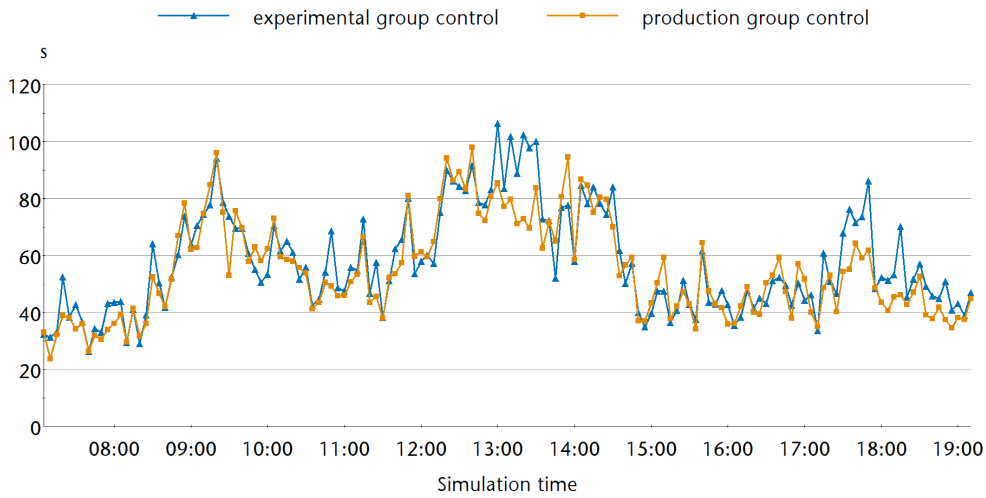

Figure 4.3: Time to destination in 2-elevator group.

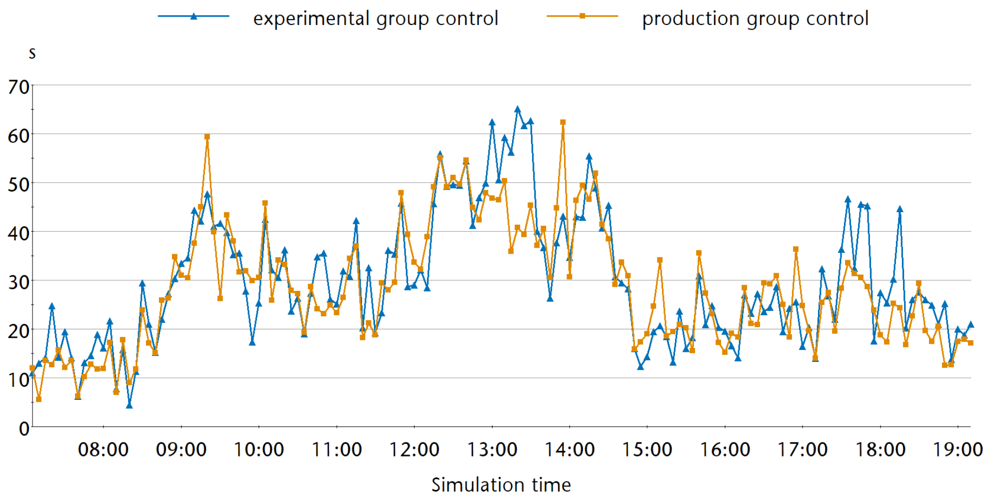

Figure 4.4: Waiting time in 2-elevator group.

4.2.2 4-elevator group

The 4-elevator group reveals some hints of the impact of the change in group control. The energy consumption time series in Figure 4.5 is largely uneventful, with the curves staying quite close to one another. However, there are some promising areas. In the early morning, just before lunchtime, and towards the end of the day from 15:00 onward, there seems to be periods of systematically lower average energy consumption with the experimental group control. For the whole day, this adds up to a 11% reduction in energy consumption. As we can see in Figure 4.6, time to destination shows little change. Overall, it increased 3%. Waiting time decreased by 10% overall. The time series of waiting time in Figure 4.7 has substantial fluctuation which makes it difficult to identify patterns. There are periods of considerably lower waiting time with the experimental group control around 9:00, at lunchtime, and in the early afternoon. It is interesting to note that during the heavy traffic at lunchtime between 11:45 and 14:30, all three objectives seem to be, on average, either reduced or unchanged.

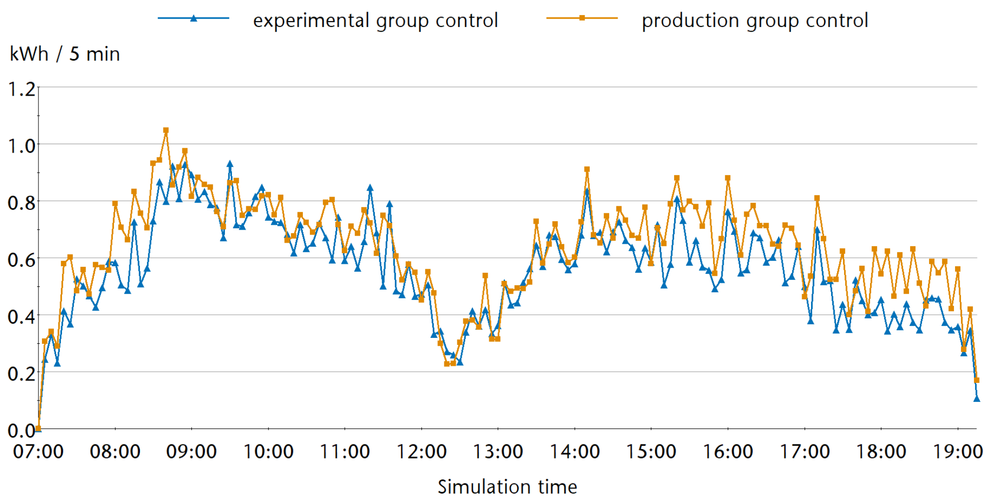

Figure 4.5: Energy consumption in 4-elevator group.

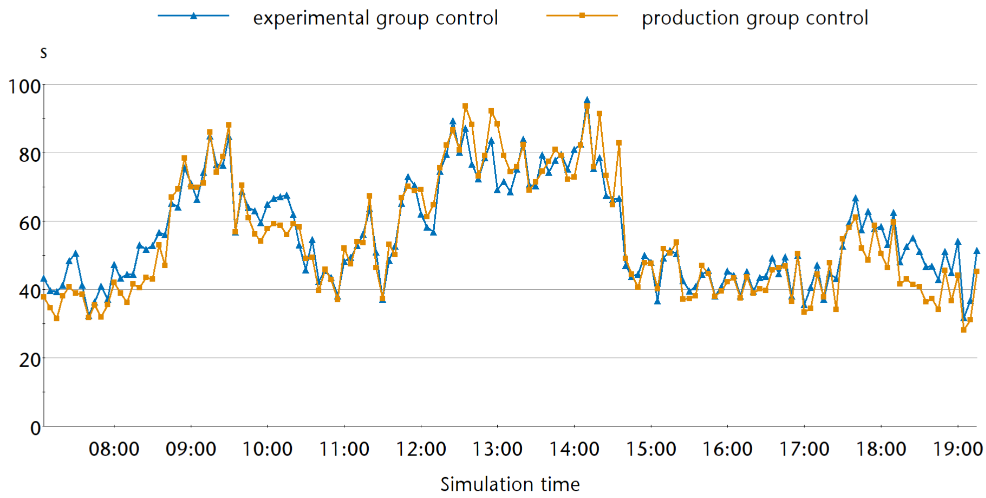

Figure 4.6: Time to destination in 4-elevator group.

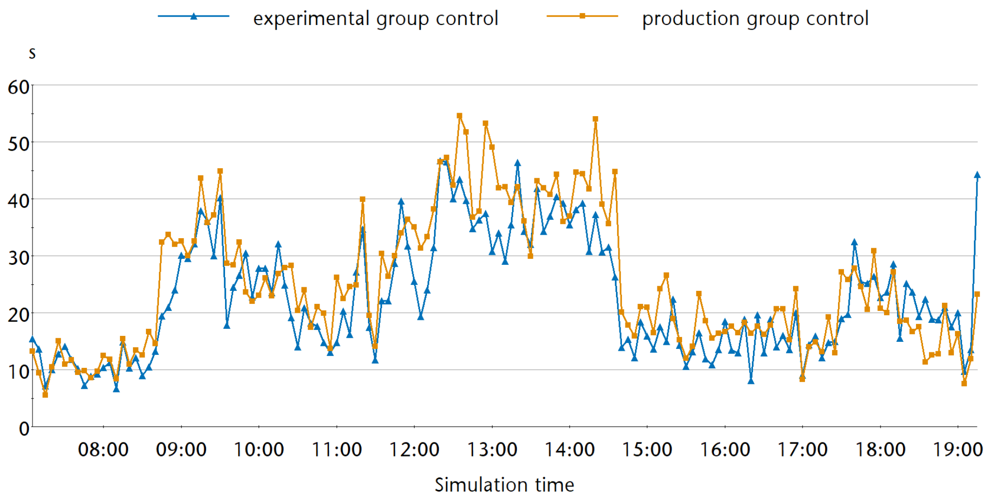

Figure 4.7: Waiting time in 4-elevator group.

4.2.3 8-elevator group

The change in group control had a clear impact in the 8-elevator group. Figure 4.8 shows lower energy consumption in all other areas except during high traffic in the morning and lunchtime. For the whole day, energy consumption was 20% lower with the experimental group control. This came at a cost of time to destination, which increased 11% overall. Figure 4.9 reveals that time to destination increased especially in the beginning and at the end of the day. There is very little change between 9:30 and 17:00. Waiting time decreased 19% overall. Figure 4.10 shows only brief periods where waiting time is not lower with the experimental group control. These periods are in early morning, late afternoon, and at lunchtime.

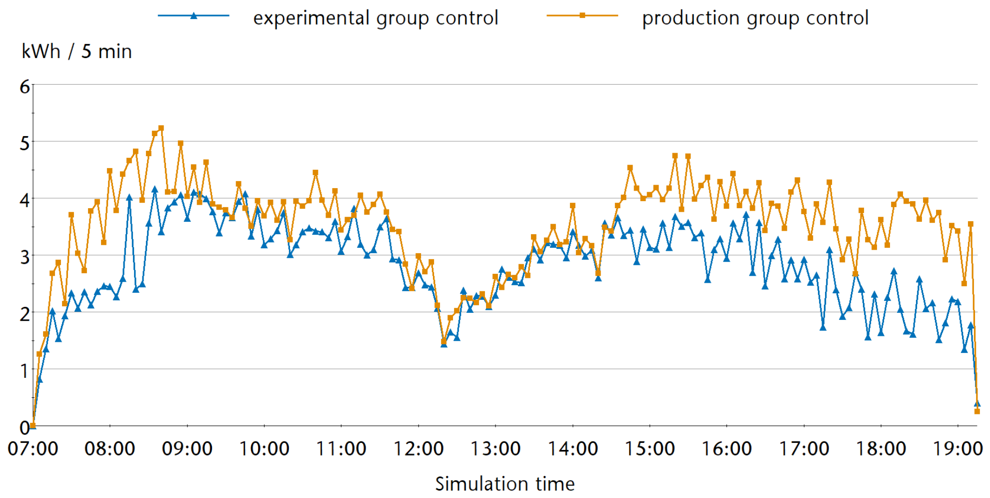

Figure 4.8: Energy consumption in 8-elevator group.

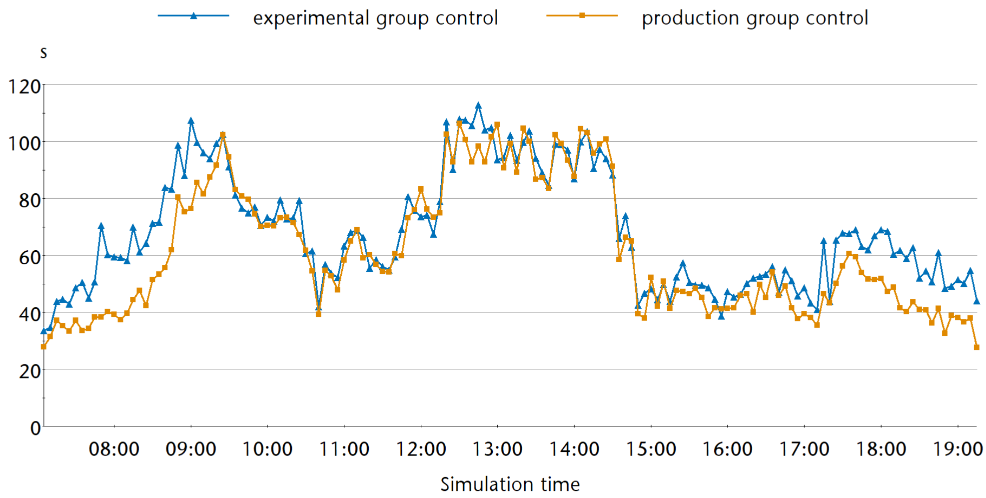

Figure 4.9: Time to destination in 8-elevator group

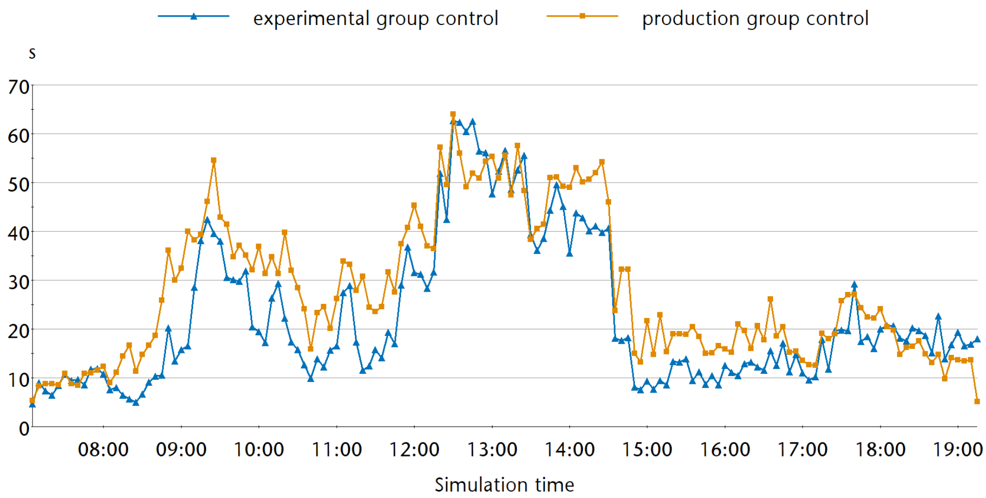

Figure 4.10: Waiting time in 8-elevator group.

4.3 Replication of production group control

In this section, we adjust the experimental group controller to replicate the behavior of the production version. To show the effects of the adjustment most clearly, simulations are run with the 8-elevator group, where the largest changes were observed in the previous section. By setting $\lambda_T = 1$ instead of the original function dependent on traffic intensity, we get the following results when comparing the experimental group controller to the production version. In Figure 4.11, we can see that there is very little change in energy consumption if the experimental group controller is adjusted in this manner. The same goes for time to destination, shown in Figure 4.12. Waiting time, shown in Figure 4.13, decreased in a few areas while remaining mostly unchanged. The reductions occurred during high traffic with a major incoming traffic component in the morning and after lunch. For the whole day, there is a 1% overall decrease in energy consumption, no change in time to destination, and a 7% decrease in waiting time.

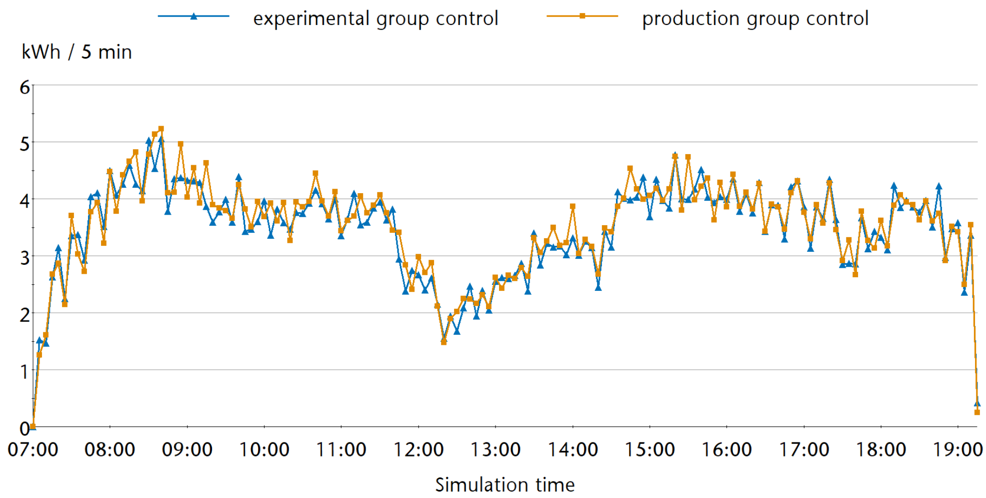

Figure 4.11: Energy consumption in 8-elevator group with the experimental group controller adjusted to replicate production version behavior.

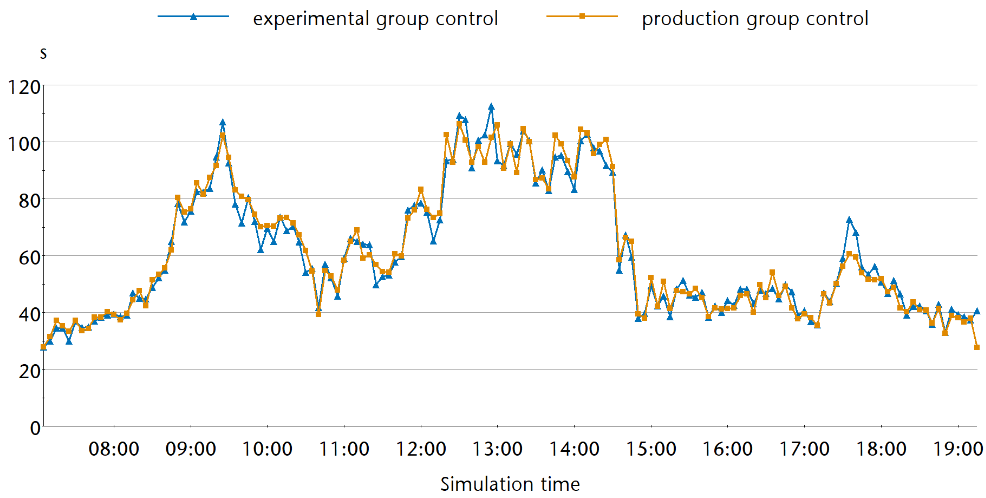

Figure 4.12: Time to destination in 8-elevator group with the experimental group controller adjusted to replicate production version behavior.

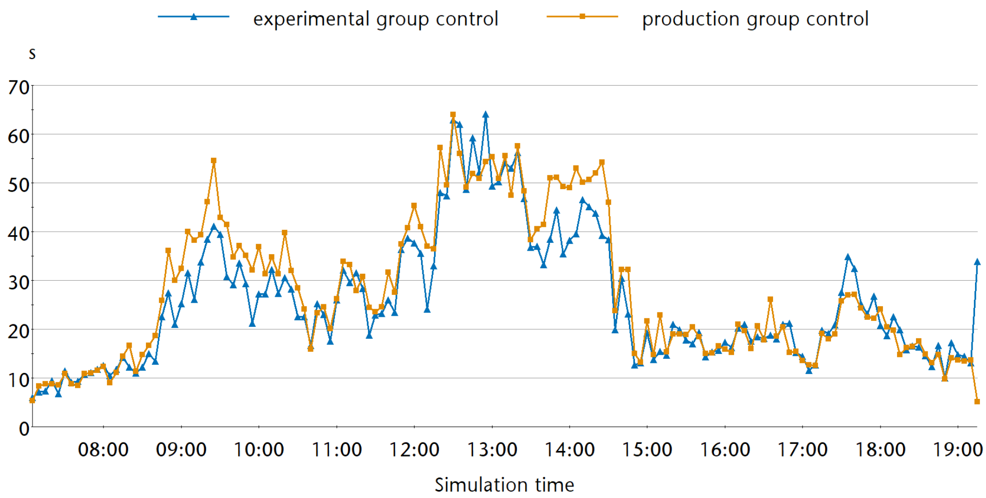

Figure 4.13: Waiting time in 8-elevator group with the experimental group controller adjusted to replicate production version behavior.

4.4 Sensitivity analysis of preference adjustment

In this section, we examine the sensitivity of the experimental group controller to changes in reference point adjustment. The reference point adjustment is changed by modifying the tuning of the parameter λ_T. Figure 3.3 shows the tuning of λ_T that was formulated in Chapter 3. That tuning will be called the standard energy saving mode in this analysis. It assumes that when the traffic intensity $I < 0.6$, we should focus on minimizing energy consumption and waiting time, and move to minimizing time to destination gradually after that. We might want to move this threshold lower, to e.g. 0.2, by using $\lambda_T(I + 0.4)$ instead of $\lambda_T(I)$. This will be called the low energy saving mode, because it minimizes energy consumption and waiting time only at the lowest traffic intensities. Correspondingly, we might want to move the threshold higher, to e.g. $I = 1$, and only move to optimizing time to destination when the traffic is already over the handling capacity of the elevator group. Then we would use $\lambda_T(I - 0.4)$ instead of $\lambda_T(I)$. This will be called the high energy saving mode. Figure 4.14 shows the tuning of λ_T based on traffic intensity in each of the three energy saving modes.

To see the effects of the difference in λ_T, simulations are run with the 8-elevator group, where the largest changes were observed in Section 4.2. We begin by examining the effects on energy consumption, shown in Figure 4.15. We can see that switching from standard to low energy saving mode increases energy consumption substantially in low traffic in the afternoon and early morning. The impact of high energy saving mode is more subtle. Some decrease in energy consumption can be seen in high traffic at lunchtime and at the end of the working day at around 17:30. Mostly the energy consumption is similar in both high and standard energy saving modes. For the whole day, switching to low energy saving mode increased energy consumption by 18%, and switching to high energy saving mode caused a 5% reduction instead.

Both modes had a clear impact on time to destination, shown in Figure 4.16. Switching to low energy saving mode decreased time to destination at both ends of the working day, with an overall decrease of 9%. Using high energy saving mode increased time to destination during high traffic at lunchtime and both ends of the working day, with an overall increase of 8%. There are also considerable changes in waiting time, shown in Figure 4.17. Low energy saving mode increased waiting time in areas outside of high traffic and both ends of the day, with an overall increase of 12%. On the other hand, high energy saving mode decreased waiting time most notably during the high lunchtime traffic, with an overall decrease of 17%.

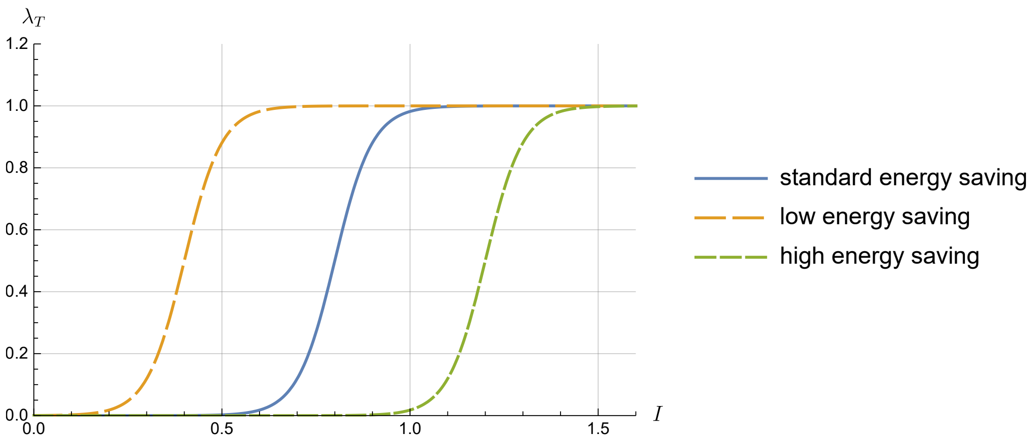

Figure 4.14: Three different energy saving modes are obtained by changing the way λ_T is tuned based on traffic intensity.

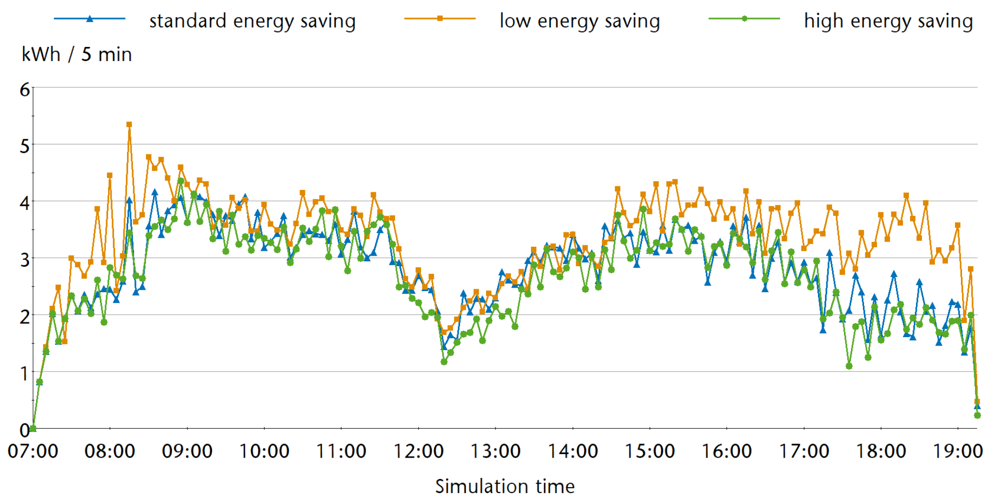

Figure 4.15: Energy consumption in 8-elevator group with the experimental group control in low, standard, and high energy saving modes.

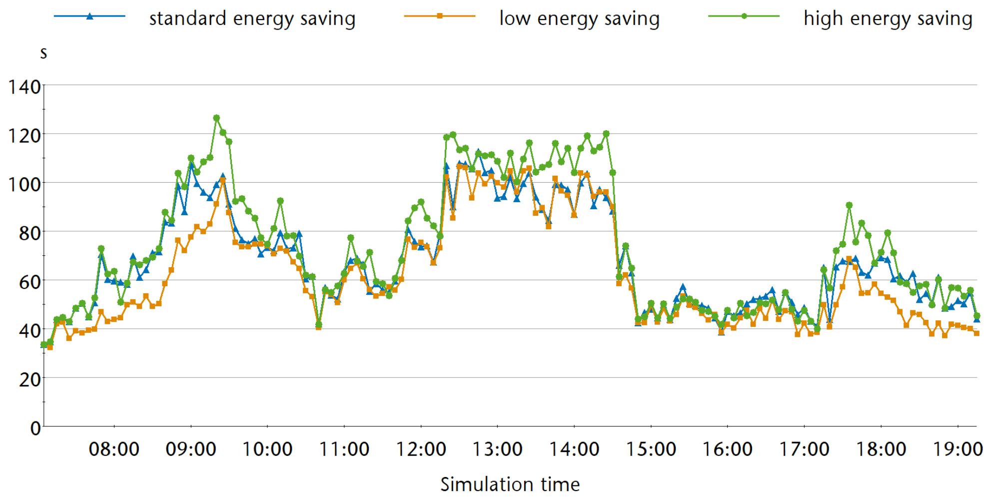

Figure 4.16: Time to destination in 8-elevator group with the experimental group control in low, standard, and high energy saving modes.

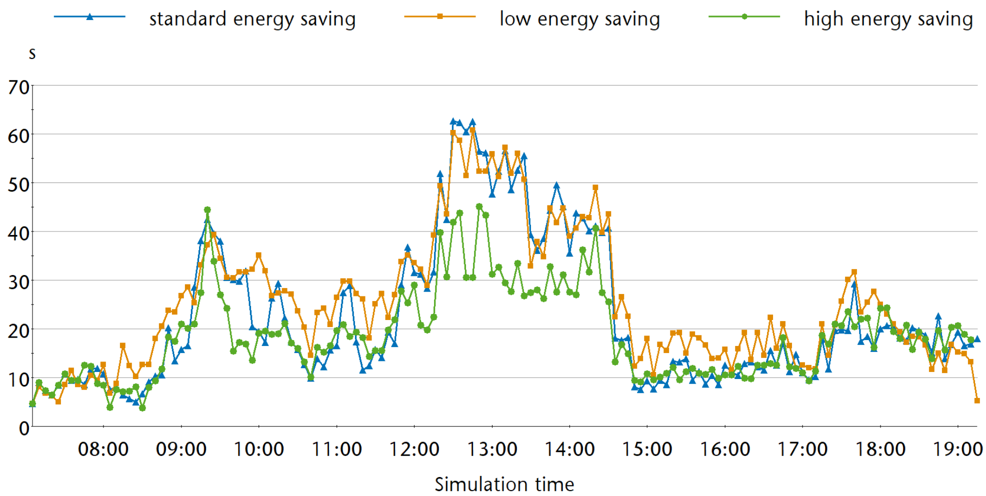

Figure 4.17: Waiting time in 8-elevator group with the experimental group control in low, standard, and high energy saving modes.

4.5 Summary and discussion

This section discusses the simulation results that were presented in detail in the previous sections. We begin with a brief summary of the results. Table 4.2 shows the overall changes that were observed in Section 4.2 when the production group control was changed to the experimental group control that includes the modifications developed in this thesis. Energy consumption decreased in all of the simulated elevator groups. More substantial reductions were observed when group size increased. Waiting time increased in the 2-elevator group but was reduced in the 4-elevator and 8-elevator groups, with a larger reduction in the latter. Overall time to destination increased in all groups. The adjustment of the experimental group controller to replicate the production version behavior, described in Section 4.3, still resulted in lower or unchanging objective values with the experimental control. Overall, energy consumption decreased 1%, time to destination did not change, and waiting time decreased 7%. Finally, Table 4.3 shows the overall changes observed in the sensitivity analysis described in Section 4.4. When the experimental group controller was adjusted to low energy saving mode, overall energy consumption and waiting time increased, and time to destination decreased. Opposite effects were observed when the experimental group controller was adjusted to high energy saving mode. By combining the results of the sensitivity analysis

Table 4.2: Change in energy consumption, time to destination, and waiting time with the shift to the experimental group control.

Number of elevators	2	4	8
Energy consumption	-4%	-11%	-20%
Time to destination	5%	3%	11%
Waiting time	5%	-10%	-19%

Table 4.3: Change in energy consumption, time to destination, and waiting time when switching the energy saving mode from standard to low or high in 8-elevator group.

Energy saving mode	low	high
Energy consumption	18%	-5%
Time to destination	-9%	8%
Waiting time	12%	-17%

and the performance analysis, we find an additional result of interest. If we were to switch the group control in the 8-elevator group directly from the production version to the experimental version in low energy saving mode, there would be a 5% reduction in overall energy consumption, and a 9% reduction in waiting time, while time to destination would increase only 1%.

In the performance analysis, larger changes were observed when group size increased. This may be because the amount of calls and call allocation alternatives increases with group size. When there are more Pareto optimal solutions to choose from, it is more likely that a change in the optimization model will change the solution chosen. A larger group gives more room for adjustment. Another possible explanation is the inaccuracy of the traffic intensity measure used in tuning the reference point. Inaccuracies in the measure that cause it to behave differently in different sized elevator groups might lead to the group controller missing opportunities for energy optimization when the traffic intensity estimate is higher than the actual intensity. Development effort could be directed to validating and improving the traffic intensity measure or to implementing traffic forecasting methods for more accurate adjustment.

The 2-elevator group results are rather surprising because of the increase in waiting time, as reductions in that objective were observed in the other two groups. The increase in waiting time seems to also contribute to the larger 5% increase in time to destination when compared with the 3% increase in the 4-elevator group. The time series of the 2-elevator group show that there is a lot of volatility in the objective values. This is natural, when the addition of a single passenger or the movement of a single car has a large impact on the average of the whole elevator group. The surprising results could just be caused by this volatility. More simulations in the 2-elevator group with different traffic patterns would be needed to provide insight about this.

Reference point adjustment based on traffic intensity seems to produce the intended results. The behavior of the experimental group controller can be seen to reflect the general preference statements introduced in Section 2.2.2. Reductions in energy consumption occurred especially during low traffic. Time to destination increased during these times but was mostly unchanged in high traffic periods. Feedback of these simulation results should be gathered to gain more preference information. With it, the parameter λ_T used in reference point adjustment could be set to better reflect the preferences of the decision maker. Adjustment accuracy might also be improved by finding a way to get estimates for the nadir and utopian values of the objectives. These could be estimated with information from previous allocations and by using the payoff table approach described in Section 2.3.1 for the nadir estimates. With these estimates, the reference point could be set in relation to the Pareto front, as first intended and described in Chapter 3, instead of the whole feasible set.

The results of the sensitivity analysis offer additional evidence about the general functionality of the reference point adjustment method. When the adjustment was changed to favor reducing energy consumption and waiting time, reductions in those objectives were observed at the cost of an increase in time to destination. When the adjustment was changed to favor reducing time to destination, reduction in time to destination was observed at the cost of increased energy consumption and waiting time. However, the sensitivity analysis was only conducted with the 8-elevator group and with limited changes in parameters. Additional testing could be done with other elevator groups and other parameter changes. Valuable insight could be gathered by, for example, testing different widths of the transition period in tuning λ_T, or by testing different ranges for moving the reference point in addition to the distance of two standard deviations introduced in Section 3.2.

In this thesis, the parameter λ_T was set as a simple function of traffic intensity. A different approach was introduced by Tyni and Ylinen (2006). They had success in using a PID controller for a similar purpose. A clear advantage of this method is its ability to make adjustments based on target levels that are monitored over many allocations. Even though the controller itself is more complex than the simple functions used here, it is more intuitive to set a target level than to determine a suitable function shape. The PID controller method could be tested and compared with the results of the current study to see if the possibilities of that method should be explored further.

When attempting to use the experimental group controller to replicate the behavior of the production version, waiting time decreased while the other two objectives were mostly unchanged. This result indicates that it is possible to reach a control behavior similar to the production version, and the production group control could be replaced without losing essential features. The result also shows that the developed call allocation method can find, at least in these limited simulations, some reductions in the three objectives without any tradeoffs in other objectives. A similar situation was observed in the performance analysis with the 4-elevator group. There it seemed that, during heavy traffic at lunchtime, waiting time decreased while energy consumption and time to destination remained mostly unchanged. It may be that during that time adjustment based on the traffic intensity estimate produced the same reference point as the adjustment used when replicating production group control behavior. This capability of finding some reductions without tradeoffs may exist because the achievement scalarizing value function can reach more Pareto optimal solutions than the additive value function of the production group control. However, we should keep in mind that these results are based only on simulations with the 8-elevator group and some additional observations with the 4-elevator group. A broader set of simulations would be needed to confirm these findings. Another limitation is that there still were some tradeoffs, even if those tradeoffs are not between the three objectives considered in this thesis. Because time to destination remained unchanged and waiting time decreased, there is by definition an increase in transit time, as shown in Figure 2.1.

One alternative for further development would be to consider waiting time as a constraint instead of an objective. This would likely create a control behavior where waiting times are often near the maximum when all effort is put in reducing energy consumption in low traffic and time to destination in high traffic. Based on the three general preference statements, it seems this might be desirable. An attractive property of this alternative is the ease of preference modeling. It is simpler for a decision maker to consider a maximal level of waiting time rather than tradeoffs between three objectives.

An interesting topic for future research would be the implementation of an additive value function and comparison of results between it and the achievement scalarizing function approach used here. As discussed in Section 2.2.2, an additive value function cannot be used to accurately model the preferences for call allocation. Despite its limitations, it might be a useful approximation, and comparisons could reveal valuable insight about the properties of the call allocation problem.

There is plenty of work still ahead before the concepts formulated in this thesis would be ready for deployment. More simulations are needed to test the performance and sensitivity of the model in different situations after this proof of concept. Additional simulations should be carried out with residential buildings, larger elevator groups, mid-rise, high-rise, and sky-rise groups, shuttle elevator groups, and double-deck elevators. Fine-tuning and testing different values for the various parameters that go into the model is also a task that is left mostly for future development.

Chapter 5

Conclusions

This thesis has developed a multiobjective optimization model for the elevator call allocation problem with three objectives: energy consumption of the elevator group, time to destination of passengers, and waiting time. The optimization model utilizes an achievement scalarizing value function to transform the multiobjective optimization problem to a single objective problem. This problem is then solved with the same genetic algorithm currently used in the production version of the call allocation system. An extension of the existing additive value function was discussed and eventually deemed inaccurate for modeling the preference relations between the three objectives. The achievement scalarizing function approach was considered to be a theoretically attractive option for the call allocation task. With it, preferences can be stated in the simple form of a reference point, an ϵ-properly Pareto optimal solution is guaranteed, any ϵ-properly Pareto optimal solution can be reached by moving the reference point, and the solution changes continuously with changes in the reference. The preferences for the solution were known on a general level, and they were dependent on the amount of traffic at the time the allocation decision was being made. Therefore, the reference point was set in relation to the feasible set of solutions based on traffic intensity.

This optimization model was tested with simulations in three different elevator groups. These were groups of two, four, and eight elevator cars in typical office buildings. A daily office traffic profile was used in the simulations. The simulations showed a decrease of energy consumption between 4 and 20% in the different elevator groups with the new model. Waiting time increased in the 2-elevator group by 5% and decreased in the other two groups by 10% and 19%. These reductions came at the cost of time to destination which increased by 3–11%. The largest changes were observed in the 8-elevator group. The results aligned on a general level with the known preferences, with most energy consumption reductions, and increases in time to destination, occurring in low traffic. The developed optimization model was also adjusted to replicate the behavior of the production version and tested in the 8-elevator group. This adjustment created a control behavior where energy consumption and time to destination were mostly unchanged in comparison to the production version, but waiting time decreased by 7% overall. A sensitivity analysis was conducted for the preference adjustment method with simulations in the 8-elevator group. In these simulations, the preference adjustment method functioned as expected.

These results are based on a limited set of simulations. In light of this, the developed solution should be seen as proof of concept rather than a perfected call allocation solution. Much more comprehensive testing, tuning, and simulating should be carried out before making definite conclusions about the viability of the solution. The simulation results show that the developed model is functional, but the performance of the model is not guaranteed in broader applications. The reductions in energy consumption and waiting time were substantial, but so were the increases in time to destination. This is in line with the general preference of focusing on reducing energy consumption in low traffic at the cost of the service level. Still, demonstrating ways to reduce energy consumption without losses in time to destination might be required to create enough demand for this type of solution. The results of the sensitivity analysis indicate that answering that need might be possible with additional fine-tuning of model parameters.

Accurate preference elicitation would be a major step in developing attractive call allocation solutions with multiple objectives. In this respect, the current study was limited by the unavailability of accurate preference information. In this situation, the ease of preference adjustment was seen as a valuable attribute of the chosen method. More accurate preference information would open possibilities for refining the model developed in this thesis or for testing entirely different solutions where the preferences can be modeled more accurately without the need for easy adjustability. An exciting opportunity in this area would be the development of new call allocation methods interactively with building managers who could be trusted to state preferences to guide the solution process. They are the primary people responsible for the functionality of the elevator system in their buildings. The only way to create more sustainable elevator systems is by discovering solutions that are both more sustainable and answer their needs better.

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