A DYNAMIC STRATEGIC PLAN FOR THE TRANSITION TO A CLEAN BUS FLEET USING MULTI-STAGE STOCHASTIC PROGRAMMING

by
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ABSTRACT

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Keywords: Bus fleet transition, Zero-emission vehicles, Sustainability, Strategic Planning, Multi-stage stochastic programming

In recent years, the transition to clean bus fleets has accelerated. Although this transition might bring environmental and economic benefits, it requires a long-term strategic plan due to the large investment costs involved. This thesis proposes a multi-stage stochastic program to optimize strategic plans for the clean bus fleet transition that explicitly considers the uncertainty scenarios in the cost and efficiency improvements of clean buses.

Our optimization model minimizes the total expected cost subject to emission targets, budget restrictions, and several other operational considerations. We propose a new forecasting approach that captures the correlation between technological improvements to obtain realistic future pathways for Battery Electric Buses (BEBs) and Hydrogen Fuel Cell Buses (HFCBs), which are then given to the multi-stage stochastic program as scenarios. We also utilize a physics-based model for BEBs to accurately capture their energy consumption and recharging needs.

As a case study, we focus on the complex public bus network of Istanbul, which aims to transition to a clean bus fleet by 2050. Utilizing real datasets, we solve a five-stage stochastic program spanning a 25-year planning horizon that involves 256 scenarios to obtain dynamic strategic plans that can be used by policymakers.

Our results suggest that BEBs are more advantageous than HFCBs, even in slow

BEB but fast HFCB development scenarios. We also conduct several sensitivity analyses to understand the effects of intermediate emission targets, budget limitations, and energy prices.

ÖZET

ÇOK AŞAMALI RASSAL PROGRAMLAMA İLE TEMİZ OTOBÜS FİLOSUNA GEÇİŞ İÇİN DİNAMİK STRATEJİK PLANLAMA

NEMAN KARIMI

ENDÜSTRİ MÜHENDİSLİĞİ YÜKSEK LİSANS TEZİ, TEMMUZ 2025

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Anahtar Kelimeler: Otobüs filosu dönüşümü; Sıfır emisyonlu araçlar; Sürdürülebilirlik; Stratejik planlama; Çok aşamalı stokastik programlama

Son yıllarda temiz otobüs filolarına geçiş hız kazanmıştır. Bu geçiş çevresel ve ekonomik faydalar sağlayabilse de yüksek yatırım maliyetleri nedeniyle uzun vadeli bir stratejik plan gerektirir. Bu tez, temiz otobüs filosuna geçişe yönelik stratejik planları eniyilemek amacıyla, temiz otobüslerin maliyet ve verimlilik artışlarındaki belirsizliği senaryolar olarak açıkça dikkate alan çok aşamalı bir rassal program önermektedir. Eniyileme modelimiz, emisyon hedefleri, bütçe kısıtları ve diğer operasyonel gereksinimler altında toplam beklenen maliyeti enküçüklemektedir.

Bataryalı Elektrikli Otobüsler (BEO'lar) ve Hidrojen Yakıt Hücreli Otobüsler (HYHO'lar) için gerçekçi gelecek yolları elde etmek amacıyla, teknolojik gelişmeler arasındaki korelasyonu yakalayan yeni bir tahmin yaklaşımı geliştirerek çok aşamalı rassal programa senaryolar olarak aktardık. Ayrıca, BEO'ların enerji tüketimini ve şarj ihtiyaçlarını doğru biçimde yansıtmak için fizik tabanlı bir model kullandık.

Vaka çalışması olarak 2050'ye kadar temiz filoya geçiş hedefleyen İstanbul'un karmaşık halk otobüsü ağı seçilmiştir. Gerçek verileri kullanarak, 25 yıllık planlama ufkunu kapsayan, beş aşamalı ve 256 senaryolu rassal programı çözerek karar vericiler için dinamik stratejik planlar elde ettik. Sonuçlarımız, BEO gelişiminin yavaş, HYHO gelişiminin hızlı olduğu senaryolarda dahi BEO'ların HYHO'lardan daha avantajlı olduğunu göstermektedir. Ayrıca ara emisyon hedefleri, bütçe sınırlamaları ve enerji fiyatlarının etkilerini incelemek üzere duyarlılık analizleri gerçekleştirdik.

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1. INTRODUCTION

Transport-related CO_2 emissions account for over 21% of global emissions, with the majority coming from internal combustion engine vehicles used in road transport (IEA, 2023b). Due to the significant impact of these emissions on climate change, ambitious targets have been set to transition the transport sector from fossil fuels to sustainable energy sources. For instance, the United States aims to eliminate all emissions in the transport sector by 2050, while the European Union pledges to reduce transport-related emissions by 90% by the same year (European Commission, 2020; Muratori, Kunz, Hula, Freedberg & others, 2023). Although the adoption of clean energy alternatives such as electric and fuel cell vehicles has increased in recent years, a lot more effort is still needed to keep the long-term net-zero emission goals within reach. This is particularly important for medium and heavy-duty vehicles such as trucks and buses, which need accelerated transitions (IEA, 2023a). Despite making up only 8% of all vehicles (excluding two- and three-wheelers), trucks and buses account for over 35% of road transport emissions (IEA, 2024b). To accelerate the shift of conventional fuel vehicles to clean technology alternatives, 33 countries have joined the Global Memorandum of Understanding on Zero-Emission Medium- and Heavy-Duty Vehicles as of 2023, committing to 30% zero-emission truck and bus sales by 2030 and 100% by 2040 (IEA, 2024a).

Such policies and pledges necessitate strategic planning to minimize the total costs of transitioning heavy-duty vehicle fleets, such as city buses. Due to the currently high investment costs of zero-emission buses—including their purchase and the costs related to building the required infrastructure— carefully constructed strategic plans could save millions of dollars. These plans should focus on identifying the most cost-effective mix of bus technologies to purchase, the most favorable infrastructure technology to utilize (such as overnight charging vs. fast charging for electric buses), and the optimal timing for bus replacements. To this end, case studies have been conducted for several cities worldwide, including cities in China (Zhang, Liu, Wang & Yu, 2022), Singapore (Zhou, Ong & Meng, 2023), Germany (Dirks, Schiffer & Walther, 2022), France (Pelletier, Jabali, Mendoza & Laporte, 2019), the US (Islam

& Lownes, 2019), and Austria (Frieß & Pferschy, 2024), to optimize the bus fleet transition to clean energy buses.

Most of the relevant studies focused on electric buses (EB) as the clean energy option. With today's technology, EBs are widely considered to be the most cost-effective zero-emission alternative. However, their integration into fleets is complicated by a number of barriers, the most significant being their limited driving range. Currently, battery electric buses (BEBs), which rely only on electricity stored in on-board batteries, are the most common type of EBs. There are different options available for BEBs in terms of battery capacity which can affect operational planning during their use. BEBs equipped with large and heavy batteries might be recharged only at night due to the long recharging time, or those that have smaller batteries can utilize fast charging stations and possibly recharge multiple times within the day to ensure demand satisfaction. Assuming that existing bus dispatch timetables are maintained, it is crucial to ensure that buses relying on overnight charging (ONC) have sufficient battery capacity to complete the scheduled trips. Moreover, fast-charging (FC) buses require an additional consideration in recharge scheduling, which depends on the frequency of assigned trips, availability of charging stations and the time needed for recharging. To this end, different studies have attempted to optimize the decisions related to the investment and placement of charger technology, investments on electric buses with different battery capacities and recharge scheduling (Perumal, Lusby & Larsen, 2022).

Hydrogen fuel cell buses (HFCBs) are also gaining attention in the literature. Although they may not yet be competitive with EBs, efforts to reduce their purchase and operational costs could make them promising options for new city buses in near future. These buses are similar to diesel buses in terms of their operation, as they usually require one daily refueling, which takes less than 10 minutes (Anandarajah, McDowall & Ekins, 2013).

Many efforts are being made to improve both BEBs and HFCBs in terms of reducing costs and increasing efficiency. For BEBs, the anticipated increase in energy density of batteries will improve their driving range, allowing them to operate on lines that were previously impractical or not cost-effective. Improvements in HFCBs are also expected to increase fuel cell efficiency, thereby decreasing fuel consumption and lowering operational costs. However, these improvements in cost and efficiency are often overlooked in strategic transition plans for bus fleets. Anticipated cost reductions are only rarely considered as yearly reductions in the purchase cost of BEBs and in a deterministic manner. Efficiency-related improvements and their implications are even more scarce in the literature. In He, Liu, Zhang & Song (2023), reductions in energy consumption of newly purchased buses and increased recharging efficiency were included, but again as deterministic parameters. In Avenali, De Santis, Giagnorio & Matteucci (2024), the uncertainty of investment costs and maximum energy consumption of BEBs was incorporated through a simulation-based approach that optimizes the timing of fleet replacements by minimizing the total cost of ownership, considering the probabilities of future technological advances. However, this method does not explicitly model technological changes as scenarios.

To the best of our knowledge, no study has included long-term technological advances in BEBs and HFCBs, which are uncertain by nature, affecting their costs and efficiency as stochastic scenarios. To fill this gap, we present an optimization model to strategically plan the bus fleet transition to clean energy technologies, treating cost- and efficiency-related technological advances in batteries and fuel cells as scenarios in a large-scale multi-stage stochastic programming model. After forecasting the advances and clustering them into scenarios in order to capture their inherent correlation, we test our model on the large bus fleet of Istanbul Municipality, which aims to transition to a clean bus fleet by 2050 as part of its Sustainable Urban Mobility Plan (Istanbul Metropolitan Municipality, 2022), with more than 6,500 buses operating on over 830 lines. We also perform sensitivity analysis to provide insights for bus fleet owners and managers.

This thesis is directly derived from the author's publication co-authored with his supervisors (Karimi, Kocuk & Yuksel, 2024).

2. RELATED WORK

2.1 Literature Review

The literature on strategic planning for transitioning to clean energy buses can be categorized into two main approaches: 'one-step transition' and 'multi-step transition.' In the one-step transition approach, strategic decisions, including investments in fleet and infrastructure, are made at a single point in time. In contrast, the multi-step transition approach involves making decisions at multiple points throughout the planning period, usually because of budget constraints or long-term emission reduction goals. This gradual transition approach is better suited for taking into account evolving technologies and changing parameters; therefore, we adopt this approach in this thesis. In what follows, we first mention some one-step transition studies before delving into the literature on multi-step transition.

Existing studies with a one-step transition approach are mostly focused on electric buses and their necessary infrastructure. Different charging technologies, including recharging at stations, lane charging, and battery swap technologies are evaluated against each other in some studies (Bi, De Kleine & Keoleian, 2017; Chen, Yin & Song, 2018). However, the majority of studies focus on charging stations and involve the deployment of fast-charging and overnight depot charging stations in their strategic plans. This includes optimal placement of fast-charging stations (Xylia, Leduc, Patrizio, Kraxner & Silveira, 2017), decisions about battery capacity (Kunith, Mendelevitch & Goehlich, 2017), and investigating the effect of factors like demand uncertainties (An, 2020) and energy consumption uncertainty (Benoliel, Jenn & Tal, 2021) on such decisions. Some researchers integrate more operational-level problems such as electric bus scheduling and charge scheduling, with strategic decisions including infrastructure planning, battery sizing and fleet sizing, see, e.g., Battaia, Dolgui, Guschinsky & Rozin (2023); Guschinsky, Kovalyov, Pesch & Rozin (2023); He, Liu & Song (2022); Rogge, Van der Hurk, Larsen & Sauer (2018); Shehabeldeen, Foda & Mohamed (2024); Wang, Huang, Xu & Barclay (2017); Yıldırım

& Yıldız (2021).

On the other hand, most studies with a multi-step approach develop optimization models similar to those for the parallel equipment replacement problem. In these models, purchasing and salvaging decisions are made in each period to minimize total costs while ensuring demand is met throughout the planning horizon. Keles & Hartman (2004) are among the first to apply such models to bus fleets, including different competing technologies. Later studies incorporate emission-related costs (Feng & Figliozzi, 2014) or constraints (Emiliano, Alvelos, Telhada & Lanzer, 2020), along with decisions for bus-to-task assignments (Stasko & Gao, 2010). Islam & Lownes (2019) include BEBs as clean technology options and account for their charger costs. An integer linear program is developed in Pelletier et al. (2019) to minimize the total costs of managing a bus fleet over a planning horizon. Different charging technologies for EBs are included in the study, and the model accounts for midlife costs incurred for replacing BEB batteries and bus-to-route assignment decisions. Tang, Li, Ceder & Wang (2021) address diesel-electric replacement ratios to manage potential fleet size increases due to range anxiety associated with BEBs.

Some recent multi-step transition studies integrate strategic decisions with various operational-level decisions. Dirks et al. (2022) address charging station deployment and battery sizing decisions, along with operational decisions such as assigning electric buses to routes and tracking battery state of charge. Zhang et al. (2022) incorporate seasonal variations in electric bus consumption into their model. Zhou et al. (2023) use an aggregated demand approach and consider external costs, including climate and health impacts, battery replacement costs, and evaluate different types of electric and hybrid buses. Li, Tang, Lin & He (2022), focus on determining charger locations, planning bus route electrification, and assigning buses to charging stations in a Build-Operate-Transfer setting. In a recent study, He et al. (2023) account for future technological advances such as reduced battery and charger costs, and improve charging efficiency in a deterministic setting. This study includes siting and sizing of fast-charging stations along with recharge schedules for new BEBs.

In Table 2.1, we compare various studies on multi-step bus fleet transition and highlighting their key aspects. To the best of our knowledge, no study has incorporated the uncertainty of future zero-emission bus (ZEB) improvements into strategic planning for bus fleet transitions in a multi-stage setting. Among these studies, Wang, Shirkoohi, Akter & Mérida (2025) is arguably the most comparable to ours, as it considers uncertainty in capital costs of bus procurements. The authors of this paper develop a two-stage stochastic mixed-integer linear program, optimizing bus procurement, route assignments, and infrastructure installment. However, their model considers only single versions of BEBs and HFCBs, and uses a two-stage approach where the first stage covers the initial two years while the second stage addresses the subsequent 13 years. In addition, they do not take into account efficiency improvements in ZEBs.

As opposed to existing literature, our multi-stage framework enables adaptive decision-making throughout the entire planning horizon while incorporating multiple vehicle configurations and route-specific energy consumption patterns. Our study captures the stochastic nature of these advancements, both in terms of cost and efficiency for BEBs and HFCBs. As both technologies are still developing, incorporating these uncertainties into planning ensures that strategies remain adaptable and cost-effective as advancements occur. The current absence of HFCBs in many strategic plans is largely due to their higher costs and lower efficiency compared to BEBs, an aspect that should be reconsidered as the future technological improvements could make HFCBs more competitive. Additionally, no study has considered the impact of route-specific energy consumption of BEBs, seasonal variations in their consumption rate, and diesel-electric replacement ratios together in strategic planning. To fill these gaps in the literature, we present a multi-stage stochastic program that incorporates technological developments while also considering detailed operational considerations, providing a comprehensive and adaptive solution for bus fleet transition planning.

Table 2.1 Studies on multi-step bus-fleet transition.

		Decisions			EB Operational Feasibility				Technological Change		
Reference	Bus Technologies	Fleet Inv.	Chg. Inv.	Task Asgn.	Elec. Cons.	Rech. Sched.	Seasonal Eff.	Diesel-electric Repl. Ratio	Cost	Eff.	Stoch.
Stasko & Gao (2010)	DB	✓	-	✓	-	-	-	-	✗	✗	✗
Feng & Figliozzi (2014)	DB/HEB	✓	-	✗	-	-	-	-	✓	✗	✗
Islam & Lownes (2019)	DB/HEB/BEB	✓	✓	✗	✗	✗	✗	✗	✓	✗	✗
Pelletier et al. (2019)	DB/CNG/BEB	✓	✓	✓	✗	✗	✗	✗	✓	✗	✗
Emiliano et al. (2020)	DB	✓	-	✗	-	-	-	-	✗	✗	✗
Tang et al. (2021)	DB/HEB/BEB	✓	✓	✗	✗	✗	✗	✓	✓	✓	✗
Li et al. (2022)	BEB	✓	✓	✓	✗	✓	✗	✓	✓	✗	✗
Dirks et al. (2022)	DB/BEB	✓	✓	✓	✗	✓	✗	✓	✓	✗	✗
Zhang et al. (2022)	DB/BEB	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗
Zhou et al. (2023)	DB/HEB/BEB	✓	✓	✗	✗	✗	✗	✗	✓	✗	✗
He et al. (2023)	BEB	✓	✓	✓	✓	✓	✗	✓	✓	✓	✗
Wang et al. (2025)	DB/BEB/HFCB	✓	✓	✓	✗	✗	✗	✗	✓	✗	✓
This thesis	DB/BEB/HFCB	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Column abbreviations. Fleet/Chg. Inv. = Fleet/Charger Investment; Task Asgn. = Task Assignment; Elec. Cons. = Electricity-consumption calculation; Rech. Sched. = Recharge Scheduling; Seasonal Eff. = Seasonal Effect; Diesel-electric Repl. Ratio = Diesel-Electric replacement ratio; Eff. = Efficiency; Stoch. = Stochasticity.
Bus codes. DB = Diesel; BEB = Battery Electric; HFCB = Hydrogen Fuel Cell; CNG = Compressed Natural Gas; HEB = Hybrid Electric.
✓ included; ✗ not included; - not applicable (no BEBs).

2.2 Our Approach and Contributions

In this thesis, we develop a multi-stage stochastic program, in which the future costs and efficiencies of competing clean technologies are represented as nodes in a scenario tree. Decisions regarding purchasing and salvaging the buses and assigning them to routes will be made on a yearly basis, and a dynamic transition plan will guide the fleet managers to make optimal decisions in each scenario throughout the planning horizon. We then test our model on a large bus fleet in Istanbul, including BEBs utilizing ONC or FC technology, as well as HFCBs. To account for operational feasibility of replacing diesel buses with electric options, we pre-calculate the energy consumed by each type and version of BEB on a given route. Using a heuristic method, we estimate the diesel-electric replacement ratio for each electric bus, on each route, and under each scenario. We provide an extensive case study involving real data collected from various sources, and conduct sensitivity analyses regarding the underlying stochastic process, the emission targets, budget limitations and energy prices. Figure 2.1 illustrates the overall framework of our study and the key steps involved in the planning process.

Our main contributions to the literature are listed as below.

- We introduce a multi-stage stochastic program for the fleet replacement problem, and investigate the effect of uncertain technological advances on the optimal long-term transition plan of vehicle fleets.
- We forecast the technological improvements of both BEBs and HFCBs in terms of cost reductions and efficiency improvements, and cluster them into a number of scenarios.
- We test our model on the large bus network of Istanbul for a 25-year planning horizon with five stages, involving details such as energy consumption calculation of several versions of BEBs on each bus line, seasonal variations in energy use, and ensuring operational feasibility by finding diesel-electric replacement ratios and recharge scheduling for FC electric buses.

We note that although we focus on a bus fleet transition problem in Istanbul, the idea of modeling technology advances as scenarios and incorporating them into a multi-stage stochastic program is applicable to other energy transition problems, emphasizing both the novelty and the generalization potential of our work.

The rest of this thesis is organized as follows: Chapter 3 provides a detailed explanation of the problem and our methodology. Chapter 4 describes the data requirements and how we obtain the parameters for our case study. Chapter 5 presents the case study and sensitivity analysis. Finally, Chapter 6 concludes the thesis.

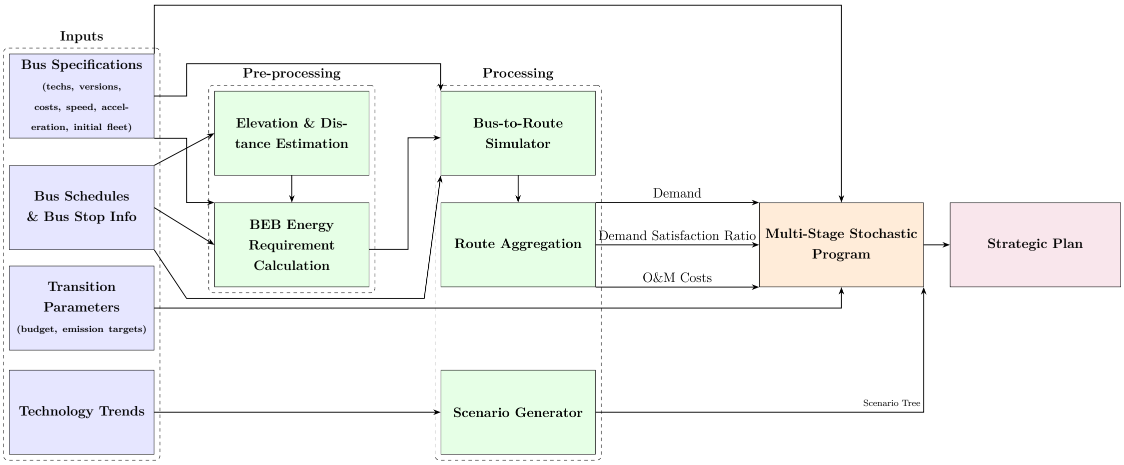


Figure 2.1 Schematic of the framework used in the study, showing input data, processing steps, and the optimization model leading to the strategic plan.

3. METHODOLOGY

3.1 Problem Description

Bus fleet operators face the challenge of determining the optimal long-term transition plan from DBs to ZEBs such as BEBs and HFCBs. The goal is to minimize the total costs of managing the fleet over a planning horizon subject to emission targets, budget limitations and other operational requirements. Let us denote $\mathcal{T} = \{0, 1, \ldots, T\}$ as the time periods in the planning horizon, where decisions on purchasing, salvaging, and assigning buses to routes are made at the beginning of each time period. Time period 0 is used to initiate the existing fleet, and no actual decisions are made in this time period. From time period 1 onwards, bus fleet operators must decide for each bus whether to keep it (if it has not reached its economic lifetime) or to replace it with one of the available bus technologies in the market.

Accounting for the technological advancements of ZEBs is essential for planning a cost-effective transition as these advancements can significantly improve performance and reduce costs. However, the uncertain nature of these advancements makes it challenging to determine the optimal timing for ZEB investments. To tackle this complex task, we introduce a multi-stage stochastic program with S stages, where each stage consists of a collection of time periods. We follow the classical scenario tree based representation (Shapiro, Dentcheva & Ruszczynski, 2021) where nodes within each stage represent possible states of all technologies over these periods in terms of cost and efficiency. Although our formulation below works for any given scenario tree $\mathcal{N}$, we specify how we construct it according to our case study in Section 4.4.

Before formally providing our formulation, we list our assumptions below:

- Each time period represents a year, as bus fleet operators typically make decisions based on the yearly budget. We further divide each year into subperiods (seasons) to account for potential differences in route demand and variations in BEB and HFCB consumption rates due to seasonal factors.

- The time periods within each stage share the same stochastic characteristics.
- Different versions may exist for each type of technology, reflecting variations such as the brand and model of the bus. For example, one version of a BEB might be a 12-meter model with a 280 kWh battery capacity, using fast-charging stations, with a 12-year lifespan, and priced at 440,000 USD.
- Investment costs of BEBs include charger cost upon purchase and battery replacement cost at their mid-life.
- All BEBs, regardless of charging type, start the day with a full battery.
- A ZEB cannot be salvaged before reaching half of its economic lifetime.
- Demand is known in advance and is deterministic.
- Assuming the passenger capacity is the same for all buses of the same length, each bus can be replaced only by another bus of the same length.
- As the cost and energy density of lithium-ion batteries (Li-ion) improve, larger batteries will be installed on BEBs while maintaining the same overall weight, but with a smaller unit cost. This will allow a BEB to cover longer distances.
- As the cost and efficiency of fuel cell systems improve, purchase cost as well as operational and maintenance (O&M) cost of HFCBs will decrease due to the fact that improved efficiency of fuel cell systems will reduce the energy consumption per unit distance.
- Recharging takes a fixed amount of time, depending on the battery capacity of the BEB versions. We assume charging power also advances alongside BEB technological improvements so that the recharging time remains consistent even after the improvement.
- Deadheading (trips with no passengers) between terminals is allowed, and buses consume less energy in such trips.

3.2 Mathematical Formulation

In this section, we present the mathematical formulation of our multi-stage stochastic program for transitioning to a clean bus fleet. The model optimizes decisions on bus purchasing, salvaging, and assignment to routes, accounting for technological advancements over the planning horizon. Tables 3.1, 3.2, and 3.3 list the index sets, parameters, and decision variables, respectively. Note that in Table 3.2, any parameter indexed by n is scenario-specific.

Table 3.1 List of index sets.

Set	**Description**	**Set**	**Description**
$\mathcal{N}$	Set of nodes, $\{0, 1, \ldots, N\}$	$\mathcal{T}$	Set of time periods, $\{0, 1, \ldots, T\}$
$\mathcal{N}_f$	Nodes in the final stage	$\mathcal{T}_n$	Time periods containing node n
$\mathcal{J}$	Set of bus types	$\mathcal{T}_{(t']}$	Time periods t s.t. $t \leq t'$ and $t + \omega_{(j,t)} > t'$
$\mathcal{K}_j$	Versions of bus type j	$\mathcal{T}_{[t')}$	Time periods t s.t. $t < t'$ and $t + \omega_{(j,t)} \geq t'$
$\mathcal{R}$	Set of routes	$\mathcal{T}_{(t')}$	Time periods t s.t. $t < t'$ and $t + \omega_{(j,t)} > t'$
$\mathcal{Q}$	Sub-periods within each period	$\mathcal{T}_{[t')^-}$	Time periods t s.t. $t + \lceil \omega_{(j,k,t)}/2 \rceil \leq t'$ and $t + \omega_{(j,k,t)} \geq t'$

Table 3.2 List of parameters.

Parameter	**Description**
π_n	Probability of node $n \in \mathcal{N}$
$\mu_{(n,t)}$	The node corresponding to the ancestor of node $n \in \mathcal{N}$ at time $t \in \mathcal{T}$
$\beta_{nominal}$	Nominal discount rate applied to time periods
ζ	Inflation rate applied to time periods
β_{real}	Real discount rate, calculated as $\beta_{real} = \frac{1+\beta_{nominal}}{1+\zeta} - 1$
β	Discount factor, calculated as $\beta = \frac{1}{1+\beta_{real}}$
$\delta^+_{(j,k,t),n}$	Investment cost of version $k \in \mathcal{K}_j$ of bus type $j \in \mathcal{J}$ purchased in time period $t \in \mathcal{T}_n$ at node $n \in \mathcal{N}$
$\delta^-_{(j,k,t),t',n}$	Salvage value of version $k \in \mathcal{K}_j$ of bus type $j \in \mathcal{J}$ purchased in time period $t \in \mathcal{T}$ and salvaged in time period $t' \in \mathcal{T}_n$ at node $n \in \mathcal{N}$
$\delta_{(j,k,t),t',r,q,n}$	O&M costs of version $k \in \mathcal{K}_j$ of bus type $j \in \mathcal{J}$ purchased in time period $t \in \mathcal{T}$ operated in time period $t' \in \mathcal{T}_n$, on route $r \in \mathcal{R}$, subperiod $q \in \mathcal{Q}$, node n
$\omega_{(j,k,t)}$	Economic life of version $k \in \mathcal{K}_j$ of bus type $j \in \mathcal{J}$ purchased in time period $t \in \mathcal{T}_n$
$\lambda_{(j,k,t),t',r,q,n}$	Demand satisfaction ratio of version $k \in \mathcal{K}_j$ of bus type $j \in \mathcal{J}$ purchased in time period $t \in \mathcal{T}$ operated in time period $t' \in \mathcal{T}_n$, route r, subperiod q, node n
$\Delta_{t,r,q}$	Demand in subperiod $q \in \mathcal{Q}$ of route $r \in \mathcal{R}$ at time period $t \in \mathcal{T}$
γ_t	Available budget for time period $t \in \mathcal{T}$
$\epsilon_{(j,k,t),t'}$	Emissions of version $k \in \mathcal{K}_j$ of bus type $j \in \mathcal{J}$ purchased in t and operated in t'
η_t	Maximum allowable emissions for time period $t \in \mathcal{T}$
$\phi_{j,k}$	Initial fleet size of version $k \in \mathcal{K}_j$ of bus type $j \in \mathcal{J}$
ψ	Maximum desired average age of the fleet at the end of the planning horizon

Table 3.3 List of decision variables.

Variable	**Description**
$v^+_{(j,k,t),n}$	Number of version $k \in \mathcal{K}_j$ of bus type $j \in \mathcal{J}$ purchased in time period $t \in \mathcal{T}_n$ and node $n \in \mathcal{N}$.
$v_{(j,k,t),t',n}$	Number of version $k \in \mathcal{K}_j$ of bus type $j \in \mathcal{J}$ purchased in time period $t \in \mathcal{T}$ and available in time period $t' \in \mathcal{T}_n$ and node $n \in \mathcal{N}$, subject to $t \le t' < t + \omega_{(j,k,t)}$.
$v'_{(j,k,t),t',r,q,n}$	Number of version $k \in \mathcal{K}_j$ of bus type $j \in \mathcal{J}$ purchased in time period $t \in \mathcal{T}$ and assigned to route $r \in \mathcal{R}$ in subperiod $q \in \mathcal{Q}$ of time period $t' \in \mathcal{T}_n$ and node $n \in \mathcal{N}$, subject to $t \le t' < t + \omega_{(j,k,t)}$.
$v^-_{(j,k,t),t',n}$	Number of version $k \in \mathcal{K}_j$ of bus type $j \in \mathcal{J}$ purchased in time period $t \in \mathcal{T}$ and salvaged in time period $t' \in \mathcal{T}_n$ and node $n \in \mathcal{N}$, subject to $t + \lceil \omega_{(j,k,t)}/2 \rceil \le t' \le t + \omega_{(j,k,t)}$.

We now present our multi-stage stochastic program as below:

$$
\begin{aligned}
\min \sum_{n=1}^{N} \pi_n \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}_j} \Bigg(& \sum_{t \in \mathcal{T}_n} \beta^{(t-1)} \delta^+_{(j,k,t),n} v^+_{(j,k,t),n} \\
& + \sum_{t' \in \mathcal{T}_n} \sum_{t \in \mathcal{T}_{(t']}} \sum_{r \in \mathcal{R}} \sum_{q \in \mathcal{Q}} \beta^{(t'-1)} \delta_{(j,k,t),t',r,q,n} v'_{(j,k,t),t',r,q,n} \\
& - \sum_{t' \in \mathcal{T}_n} \sum_{t \in \mathcal{T}_{[t')}} \beta^{(t'-1)} \delta^-_{(j,k,t),t',n} v^-_{(j,k,t),t',n} \Bigg)
\end{aligned} \tag{3.1a}
$$

s.t.

(3.1b)
$$\sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}_j} \sum_{t \in \mathcal{T}_{(t']}} \lambda_{(j,k,t),t',r,q,n} \; v'_{(j,k,t),t',r,q,n} \ge \Delta_{t',r,q}, \quad n \in \mathcal{N}, t' \in \mathcal{T}_n, r \in \mathcal{R}, q \in \mathcal{Q}$$

(3.1c)
$$\sum_{r \in \mathcal{R}} v'_{(j,k,t),t',r,q,n} \le v_{(j,k,t),t',n}, \quad n \in \mathcal{N}, t' \in \mathcal{T}_n, t \in \mathcal{T}_{(t']}, j \in \mathcal{J}, k \in \mathcal{K}_j, q \in \mathcal{Q}$$

(3.1d)
$$v_{(j,k,t),t,n} = v^+_{(j,k,t),n}, \quad n \in \mathcal{N}, t \in \mathcal{T}_n, j \in \mathcal{J}, k \in \mathcal{K}_j$$

(3.1e)
$$v_{(j,k,t),t',n} = v_{(j,k,t),t'-1,\mu_{(n,t'-1)}} - v^-_{(j,k,t),t',n},$$
$$n \in \mathcal{N} \setminus \{0\},\ t' \in \mathcal{T}_n,\ t \in \mathcal{T}_{(t']},\ j \in \mathcal{J},\ k \in \mathcal{K}_j$$

(3.1f)
$$v^-_{(j,k,t),t',n} = v_{(j,k,t),t'-1,\mu_{(n,t'-1)}},$$
$$n \in \mathcal{N} \setminus \{0\},\ t' \in \mathcal{T}_n,\ t \in \mathcal{T}_{(t']},\ j \in \mathcal{J},\ k \in \mathcal{K}_j,\ t' = t + \omega_{(j,k,t)}$$

(3.1g)

$$\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}_j} \delta^+_{(j,k,t),n}\ v^+_{(j,k,t),n} \le \gamma_t, \quad n\in\mathcal{N}, t\in\mathcal{T}_n$$

(3.1h)

$$\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}_j}\sum_{t\in\mathcal{T}_{(t']}}\sum_{r\in\mathcal{R}}\sum_{q\in\mathcal{Q}} \epsilon_{(j,k,t),t'}\ v'_{(j,k,t),t',r,q,n} \le \eta_{t'}, \quad n\in\mathcal{N}, t'\in\mathcal{T}_n$$

(3.1i)

$$v^+_{(j,k,0),0} = \phi_{j,k},\ v^-_{(j,k,0),0,0} = 0, \quad j\in\mathcal{J}, k\in\mathcal{K}_j$$

(3.1j)

$$\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}_j}\sum_{t\in\mathcal{T}_{(T]}} (T-t+1)\ v_{(j,k,t),T,n} \le \psi \sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}_j}\sum_{t\in\mathcal{T}_{(T]}} v_{(j,k,t),T,n}, \quad n\in\mathcal{N}_f$$

(3.1k)

$$v^+_{(j,k,t),n} \in \mathbb{Z}_+, \quad n\in\mathcal{N}, t\in\mathcal{T}_n, j\in\mathcal{J}, k\in\mathcal{K}_j$$

(3.1l)

$$v^-_{(j,k,t),t',n} \in \mathbb{Z}_+, \quad n\in\mathcal{N}, t'\in\mathcal{T}_n, t\in\mathcal{T}_{[T)}, j\in\mathcal{J}, k\in\mathcal{K}_j$$

(3.1m)

$$v_{(j,k,t),t',n} \in \mathbb{Z}_+,\ v'_{(j,k,t),t',n} \in \mathbb{Z}_+, \quad n\in\mathcal{N}, t'\in\mathcal{T}_n, t\in\mathcal{T}_{(T]}, j\in\mathcal{J}, k\in\mathcal{K}_j.$$

The terms in the objective function (3.1a) represent the expected investment costs of the buses, the expected operational and maintenance costs, and the expected salvage revenue, respectively. Constraints (3.1b) require that the number of buses assigned to a route in each time period and node meets the required demand. We define demand as the number of DBs required to fulfill the current bus schedule provided by IETT. The demand satisfaction ratio is set to 1 for DBs and HFCBs. This parameter allows for adjustments in fleet size when using BEBs, which may have range limitations. For example, a specific version of BEBs may need 10 buses to operate a route that would require only 8 DBs, so its demand satisfaction ratio is set to 0.8. Constraints (3.1c) specify that the number of assigned buses should not exceed the number of buses available. Constraints (3.1d) and (3.1e) maintain the balance of buses for each type and version in every time period. Constraints (3.1f) ensure that the buses will be salvaged once they reach their economic lifetime. Constraints (3.1g) restrict the total purchasing costs to stay within the allocated budget for each time period, and constraints (3.1h) ensure that emissions remain within the limits for each time period. Constraints (3.1i) define the initial fleet size for each type and version of the bus, and make sure that no buses are salvaged at stage 0. To mitigate end-of-horizon effects, constraints (3.1j) limit the average age of the buses at the end of the planning horizon. Finally, constraints (3.1k), (3.1l), and (3.1m) ensure that decision variables take non-negative integer values.

3.3 Energy Requirement Calculation

In order to ensure operational feasibility of assigning buses to routes, and optimizing the assignment decisions, it is crucial to account for the amount of energy consumed by each version of BEBs on scheduled trips of different routes. We now present our physics-based approach to calculate the energy requirement of a specific BEB assigned to a given service trip, which impacts the O&M costs and the demand satisfaction ratio parameters. This approach accounts for route-specific characteristics such as stop frequency and elevation changes, as well as variations in energy usage due to changes in speed and braking. Table 3.4 provides the notations used in this section.

Table 3.4 List of parameters for traction power and battery power calculations.

Parameter	**Description**	**Parameter**	**Description**
f_r	Rolling resistance coefficient	ρ_{air}	Air density (kg/m^3)
C_D	Drag coefficient	g	Gravitational acceleration (m/s^2)
A_f	Frontal area of the bus (m^2)	η_t	Transmission efficiency
η_m	Motor and inverter efficiency	η_{rb}	Regenerative braking efficiency
m	Mass of the bus (kg)	m_{eq}	Equivalent mass (kg)
α	Road grade (rad)	$a(\tau)$	Bus acceleration rate at time τ (m/s^2)
$v(\tau)$	Speed of the bus at time τ (m/s)	$P_w(\tau)$	Traction power at time τ (W)

To calculate the energy requirement for a bus on a specific service trip, we first divide the trip into a set $\mathcal{S}$ of segments, where each segment represents the path between two consecutive bus stops. We assume that the bus will accelerate between the time interval $[0, \tau_1]$ with a constant rate of $\tilde{a} > 0$, maintain a constant speed between $[\tau_1, \tau_2]$, and decelerate with rate $-\tilde{a}$ between $[\tau_2, \tau_1 + \tau_2]$. For each segment, we minimize the duration $\tau_1 + \tau_2$ to cover its distance subject to the constraints on maximum speed and maximum power, where the *traction power* $P_w(\tau)$ at time τ is calculated as

$$P_w(\tau) = \Big(mg\sin(\alpha) + f_r mg\cos(\alpha) + 0.5\rho_{\text{air}} C_D A_f v(\tau)^2 + m_{\text{eq}} a(\tau)\Big)\, v(\tau).$$

Here, traction power $P_w(\tau)$ refers to the power required at the wheels to overcome resistance forces acting on the bus when traveling at a speed of $v(\tau)$, and accelerate an equivalent mass of m_{eq}, which accounts for the inertial resistance of the rotating masses in the vehicle, with an acceleration of $a(\tau)$. Required traction power is provided by the battery at a higher rate due to losses at the electric motor and transmission elements before reaching the wheels. In addition, during braking or travelling downhill, BEBs can recuperate some of the power that otherwise would be lost as heat via their regenerative braking system. The power required from the battery during traction (or recuperated by the battery during regenerative braking) $P_{\text{bat}}(\tau)$ is given by

$$P_{\text{bat}}(\tau) = \begin{cases} \frac{P_w(\tau)}{\eta_t \eta_m}, & \text{if } P_w(\tau) \geq 0 \\ P_w(\tau) \cdot \eta_t \cdot \eta_m \cdot \eta_{\text{rb}}, & \text{if } P_w(\tau) < 0 \end{cases}.$$

To find the energy requirement E_{s} of segment s, we integrate $P_{\text{bat}}(\tau)$ over the segment duration as $E_{\text{s}} = \int_0^{\tau_1+\tau_2} P_{\text{bat}}(\tau)\, d\tau$. Finally, the total energy required during the trip is the sum of the energy requirements for all segments, computed as $E_{\text{trip}} = \sum_{s \in \mathcal{S}} E_{\text{s}}$. We also account for the variation in energy requirements due to seasonal changes by multiplying the nominal consumption value by a constant that depends on the ambient temperature. We provide the details of power and energy calculations in the Appendix.

3.4 Bus-to-Route Simulator

We develop a simple simulator, Algorithm 1, to estimate key parameters if a version k of bus type j is assigned to a certain route r in a subperiod q. Since the outcome of such an assignment changes over the planning horizon due to technological advances, we run this algorithm for every node n in the scenario tree offline before solving our optimization model.

Inputs of the Bus-to-Route Simulator are the specifications of a bus (such as the type, version, charging scheme in case of BEBs, energy consumption, etc.) and the characteristics of the route (such as the trip schedule, road profile, etc.). The simulator aims to minimize the necessary number of buses in a heuristic manner for each assignment while considering operational feasibility of each bus type.

The algorithm outputs the number of necessary buses and their daily task assignments, using which we obtain several parameters for our optimization model: i)

Algorithm 1: Bus-to-Route Simulator.

```
Input: Bus parameters, trip schedule, trip information, terminal-terminal trip
       information
Output: Bus assignments, recharge details for fast-charging (FC) BEBs,
        deadheading details
for each trip in the scheduled trips do
    if no buses are yet assigned then
        Assign the first bus to the first trip. Move on to the next trip.
    else
        for each assigned bus do
            if the bus's garage location and length match with that of the scheduled
              trip and the bus can reach the trip's start point on time after
              completing its previous trip, considering deadheading then
                if bus is electric then
                    if battery is insufficient for the trip then
                        if bus type is ONC then
                            Skip this bus due to insufficient battery.
                        else if bus type is FC then
                            if the bus can start the trip with the recharge time
                              added then
                                if bus has enough energy to get to the starting point
                                  of the trip then
                                    Plan a recharge at the starting point of the trip.
                                else
                                    Plan a recharge where the bus finishes its
                                      previous assigned trip.
                                Record recharge details (location, start and end
                                  times). Assign the trip to the bus. Update
                                  cumulative energy consumed. Reset battery
                                  capacity. Move on to the next trip.
                            else
                                Skip this bus due to insufficient time for recharging.
                Assign the trip to this bus. if bus is electric then
                    Update cumulative energy consumed. Update remaining
                      battery capacity.
                Move on to the next trip.
            else
                Skip this bus.
    if no current buses can be assigned then
        Assign a new bus to this trip.
for each bus do
    Calculate the assigned distances and energy consumed (if bus is electric),
      including deadheading. if the total assigned distance is less than 10 km then
        Disregard that bus.
Record recharge summary for all fast-charging electric buses and all locations.
```

Demand satisfaction ratio (DSR) $\lambda_{(j,k,t),t',r,q,n}$, defined as the number of DBs needed divided by the number of buses needed of a specific type-version pair. ii) Charger-to-bus ratio for fast-charging BEBs, in the calculation of investment cost $\delta^{+}_{(j,k,t),n}$. iii) Average daily distance covered, in the calculation of O&M cost $\delta_{(j,k,t),t',r,q,n}$.

4. DATA COLLECTION AND PROCESSING

In this chapter, we present the data used in our case study in Chapter 5. We start by discussing the bus network data provided by the public bus fleet operator of Istanbul in Section 4.1, including a description of the preprocessing steps. Section 4.2 details the initial bus-specific cost information included in our case study. In Section 4.3, we provide the data required for forecasting future technological advancements in BEBs and HFCBs, along with an explanation of our forecasting approach. Finally, in Section 4.4, we explain how the scenarios of our stochastic program are obtained using the resulting projections. We note that the Appendix contains more detailed datasets, analyses and results.

4.1 Public Bus Transit in Istanbul

The buses operated by the Istanbul Electricity, Tram and Tunnel Establishments (IETT), the authority responsible for public bus transportation in Istanbul, carry nearly 5 million people daily and cover approximately 1.2 million kilometers (IETT, 2023). IETT provided us the following datasets:

1.1 Trip Schedule: This dataset includes the details of service trips scheduled for both March 15, 2023 (Winter Schedule) and August 3, 2023 (Summer Schedule). The summer schedule is assumed to be used only for 92 days during the summer, while the winter schedule is utilized for the remainder of the year. The specific information provided in this dataset is the route code, trip ID, scheduled route start times, scheduled distance, vehicle depot (when available) and vehicle length group.

1.2 Stop Sequence with Coordinates: This dataset provides the sequence of stops for each route and route type, along with their latitudes and longitudes.

1.3 Vehicle Information: This dataset includes information on 3,351 buses operated by IETT, detailing the number of buses at each depot, along with their brand, model, and manufacturing year. It does not cover 3,076 buses under a private bus brand of IETT, for which the detailed data is not available.

We process the above datasets to obtain the following pieces of information.

2.1 Estimation of Missing Distances: As we do not have the full information about the specific routing of each vehicle, we estimate some distances related to the deadheading services using the Haversine approximation when needed in Algorithm 1 in addition to the distance between consecutive stops.

2.2 We use the Open-Elevation API (Open-Elevation API, 2020) to determine the elevation of each stop.

2.3 Estimation of Travel Time: Through our preliminary study and dataset received from IETT, we determine that the average speed of buses is approximately 25 km/h. Consequently, we assume a maximum speed of 30 km/h.

2.4 Calculating Bus Demand: We run our simulator, Algorithm 1, to estimate the number of buses needed of each version to meet the scheduled trips in each route, for both summer and winter schedules. We present the summary of results in Table 4.1 for DBs. As the total number of buses owned by IETT in 2023 is reported to be 6,652 (IETT, 2023) the algorithm provides a reliable estimation of the actual demand.

Table 4.1 Total demand by bus length for summer and winter schedules for DBs.

Bus Length (m)	**6.5-8**	**8-9**	**10-11**	**11-14**	**14-19**	**Total**
Summer Schedule	269	23	15	4349	1418	**6071**
Winter Schedule	280	26	12	4540	1695	**6553**

2.5 Route Aggregation: As a preprocessing step, we aggregate routes based on a metric related to the DSR parameter introduced in Section 3.4. For each route, we calculate the minimum DSR for each BEB version across all bus lengths and seasons using today's technology. These minimum DSRs are then averaged across all BEB versions to create a single metric for each route. Routes are then grouped into 12 clusters based on this metric as follows: $\{\{1.00\}, [0.95, 1.00), [0.90, 0.95), \ldots, [0.50, 0.55), [0.38, 0.50)\}$. As an example, cluster with the metric of 1.00 represents the routes where even the BEB with the smallest battery capacity can cover the scheduled trips in all seasons and all bus length groups used. Since only 13 routes have a metric smaller than 0.50, we group them together into one cluster. After clustering the routes,

Table 4.2 Purchase costs (USD) for DBs and fast charging BEBs.

Model Length	DB	BEB Fast Charging 140 kWh	210 kWh	280 kWh	350 kWh	420 kWh
8m	135,000	305,000	340,000	-	-	-
10m	170,000	340,000	375,000	410,000	-	-
12m	200,000	370,000	405,000	440,000	475,000	-
18m	300,000	470,000	505,000	540,000	575,000	610,000

we calculate the DSR parameters for each cluster, assuming that all routes within a cluster share the same demand satisfaction ratio. This is done by taking the weighted average DSR of all routes within the cluster, where the weights correspond to the number of buses required for each route. The demand satisfaction ratios for buses, determined by the year of purchase, the year of operation, the specific subperiod, and the corresponding node, are all calculated using this approach.

4.2 Initial Bus-Specific Costs

We consider four bus models across different length groups: an 8m model for the 6.5-8m group, a 10m model for both the 8-9m and 10-11m groups, a 12m model for the 11-14m group, and an 18m model for the 14-19m group. Bus purchase costs are estimated from recent tenders in Turkey and Europe, information gathered from local bus manufacturers and technical reports, and given in Table 4.3. The investment costs of BEBs include battery replacement and charger costs, in addition to the bus purchase costs. We assume that each BEB requires one battery replacement at the end of year six of its operation that is adjusted for the discount rate. The initial battery pack cost, denoted by BC, is assumed to be 500USD/kWh. For charging infrastructure, our study includes regular chargers with 50kW charging power, priced at 20,000 USD per unit for ONC buses, and fast chargers with 350kW charging power, priced at 45,000 USD per unit for fast charging buses. Each ONC bus requires one dedicated charger while charger-to-bus ratio for FC buses with a specific version is estimated using Algorithm 1 and the total charger cost is distributed across all buses. Recharging times for FC buses are based on a full recharge, assuming a 90% charging efficiency. Finally, we assume that salvage values depreciate yearly by 15% for all buses.

Table 4.3 Purchase costs (USD) for overnight charging BEBs and HFCBs.

Model Length	BEB Overnight Charging 280 kWh	350 kWh	420 kWh	490 kWh	560 kWh	HFCB
8m	375,000	410,000	-	-	-	500,000
10m	410,000	445,000	480,000	-	-	600,000
12m	440,000	475,000	510,000	545,000	-	700,000
18m	540,000	575,000	610,000	645,000	680,000	1,000,000

The O&M costs include energy, maintenance, and driver costs. We use Algorithm 1 to determine the average daily distance the buses of a specific version cover when assigned a specific route. This information along with the average energy requirement for BEBs is used to calculate the total energy costs and maintenance costs, where the unit costs are given in Table 4.4. We assume that the energy consumption estimation is done in spring/fall, and increase BEB and HFCB consumption rates by 15% for winter and 5% for summer, consistent with Istanbul's climate. Regarding the driver cost, the information gathered from IETT Activity Reports and Financial Statements suggest that the approximate salary is nearly double the minimum wage. Additionally, the number of drivers is about 20% more than the number of buses. Therefore we calculate the driver cost per bus as $2 \times 1.2 = 2.4$ times the minimum wage, approximately 40 USD/day.

Bus Type	Energy Use	Maintenance	Energy Cost
DB	0.435 L/km (Ma, Miao, Wu & Liu, 2021)	0.58 USD/km (Holland, Mansur, Muller & Yates, 2021)	1.29 USD/L (Petrol Ofisi, 2024)
BEB	Route/version–dependent –	0.34 USD/km (Holland et al., 2021)	0.16 USD/kWh (EPDK, 2024)
HFCB	0.09 kg/km (Ajanovic, Glatt & Haas, 2021)	0.29 USD/km (Collins & Post, 2022)	10.00 USD/kg –

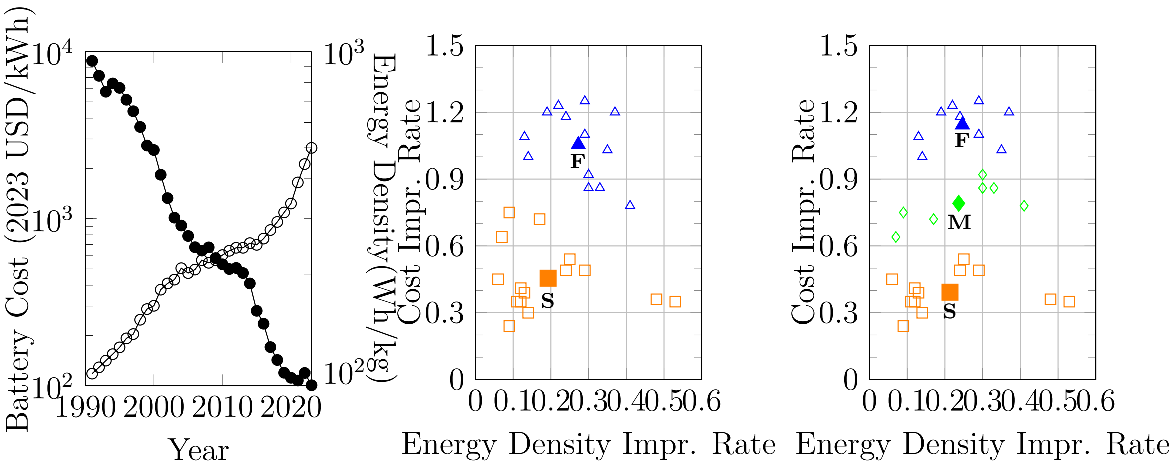
Table 4.4 Maintenance costs, energy consumption and energy costs for all bus types.

4.3 Technological Change Forecasts

In this section, we examine the cost and efficiency trends of BEBs and HFCBs. We quantify these trends for each year with respect to five years prior, consistent with our case study (Chapter 5). Specifically, for each year, the efficiency improvement rate is calculated as the natural logarithm of the year's value divided by the value from five years earlier, while cost improvement is calculated as the negative logarithm of the same ratio. We then plot the scatter plot of these improvement rates, which highlights distinct patterns and trends across five-year periods. Clustering techniques are applied to group the data points based on their similarities, with each cluster representing a possible scenario of technological advancement. The probabilities associated with each cluster indicate the proportion of data points that belong to that cluster.

4.3.1 BEB Technological Change

The cost of Li-ion batteries per kilowatt-hour has significantly decreased over the years while their energy density has steadily increased. Figure 4.1a presents the data on energy density and battery cost from 1991 onwards, extracted from the charts in reference (Walter, Bond, Butler-Sloss, Speelman, Numata & Atkinson, 2023) using the WebPlotDigitizer tool (Autometris, 2023). Given the cost and energy density values, we compute the five-year improvement ratios as described above. Then, these ratios are clustered into two and three different groups by minimizing the sum of squared Euclidean distances between each data point and its assigned cluster centers can be seen in Figures 4.1b and 4.1c. As an example, let us consider the two-cluster setting, in which case the probabilities for the fast improvement cluster (**F**) and the slow improvement cluster (**S**) are 0.46 and 0.54, respectively. In fast improvement cluster, the energy density and cost improvement rates are 0.27 and 1.05, respectively. Taking the exponential of these rates, we get an energy density multiplier of 1.31 and a cost multiplier of 0.35.



(a) Cell cost (left, solid circle) vs. energy density (right, hollow circle) in log-scale.

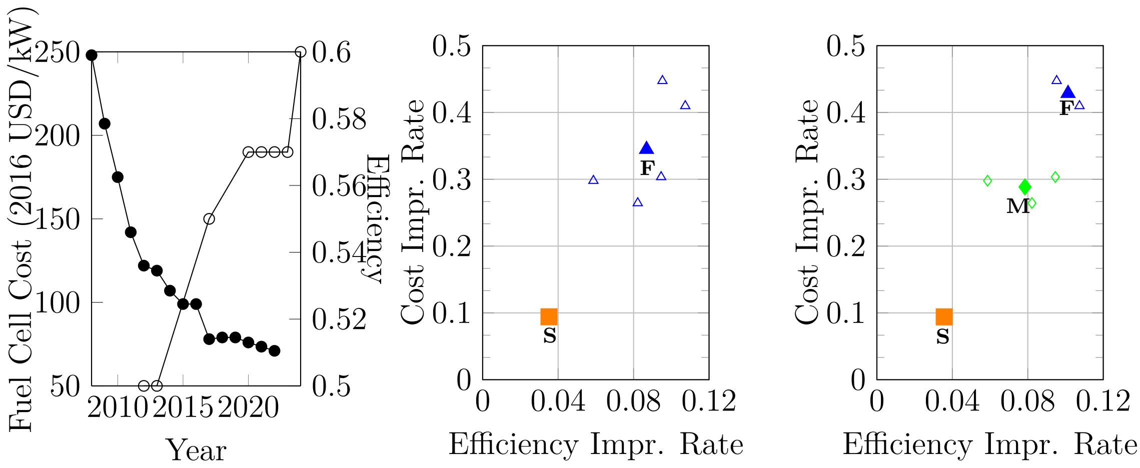
(b) Five-year energy density vs. cost improvement rates for BEBs with two clusters.

(c) Five-year energy density vs. cost improvement rates for BEBs with three clusters.

Figure 4.1 BEB technology improvement charts. Cluster centers are marked with solid marks in (b) and (c), and can be distinguished by the abbreviations of **S**low, **F**ast and **M**edium.

4.3.2 HFCB Technological Change

Fuel cell systems used in HFCBs have also improved in terms of cost and efficiency. However, since these systems are only being used for heavy duty purposes recently, the data is scarce. Instead, we use the cost figures for light duty fuel cell systems (Huya-Kouadio & James, 2023) and the efficiency of a specific producer (Ballard) as a proxy as shown in Figure 4.2a. We then follow a similar approach to Li-ion batteries: We compute five-year cost and efficiency improvements (for the common years in two datasets), and obtain the clusters in Figures 4.2b and 4.2c.



(a) Fuel cell system cost (left, solid circle) vs. efficiency (right, hollow circle).

(b) Five-year efficiency vs. cost improvement rates for HFCBs with two clusters.

(c) Five-year efficiency vs. cost improvement rates for HFCBs with three clusters.

Figure 4.2 HFCB technology improvement charts.

4.4 Scenario Tree Generation

We now formalize how we obtain the scenarios of our multi-stage stochastic program using the technological change forecasts. Our approach is built on a two-step procedure: In the first step, we obtain *technology trees* for each bus type illustrating future projections while in the second step, we combine these individual projections to build the scenario tree.

Let us start with the first step. For a bus technology $j \in \mathcal{J}$, let us denote its cost and efficiency improvement multipliers for each stage by random variables Θ^c_j and Θ^e_j. These multipliers are assumed to be independent across different technologies, but may be correlated within the same technology, which is why we cluster them as explained in Section 3.3, to capture their inherent correlations. We will assume that each pair of random variables take values from a joint discrete probability distribution with a sample space consisting of elements $(\Theta^c_{jb}, \Theta^e_{jb})$ w.p. Θ^p_{jb}, $b = 1, \dots, B_j$. At each node $\ell \in \mathcal{L}$ of the technology tree, we denote $\theta^c_{j\ell}$ as the relative cost change, $\theta^e_{j\ell}$ as the relative efficiency change, and $\theta^p_{j\ell}$ as the probability of node ℓ.

In particular, for a technology j with a given support size B_j, we use the clustering approach from Section 4.3 with B_j clusters, and use efficiency and cost multipliers of each cluster b as $(\Theta^c_{jb}, \Theta^e_{jb})$ values and the fraction of points in each cluster b as Θ^p_{jb}. We run Algorithm 2 to construct a perfect B_j-ary tree denoted by $\mathcal{N}(j)$, which we will call as the technology tree.

Algorithm 2: Technology Tree Construction Algorithm

Input: Improvement distribution of technology j, the number of stages S.
Output: Technology tree.

```
Set θ^c_{j1} = θ^e_{j1} = θ^p_{j1} = 1, ID = 1 and L = {1}.
for s = 1, ..., S − 1 do
    Set L' = ∅.
    for ℓ ∈ L do
        for b = 1, ..., B_j do
            Set ID = ID + 1, h = ID.
            Set θ^c_{jh} = θ^c_{jℓ}Θ^c_{jb}, θ^e_{jh} = θ^e_{jℓ}Θ^e_{jb}, θ^p_{jh} = θ^p_{jℓ}Θ^p_{jb}.
            Set L' = L' ∪ {ID}.
    L = L'.
```

Figure 4.3 illustrates exemplary technology trees for DBs, BEBs and HFCBs for $S = 2$ stages with respect to the data reported in Section 4.3.

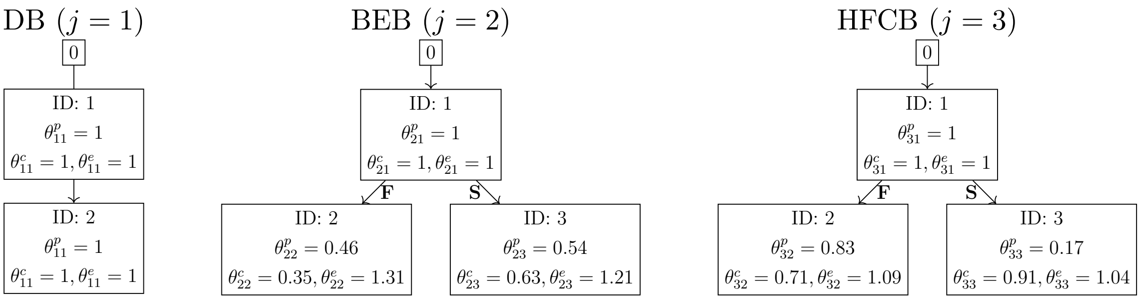


Figure 4.3 Technology trees of DB ($B_1 = 1$), BEB ($B_2 = 2$) and HFCB ($B_3 = 2$) with $S = 2$ stages.

In the second step, once the technology trees are at hand for each $j \in \mathcal{J}$, we obtain the scenario tree $\mathcal{N}$ by taking the Cartesian product of each node of the technology tree $\mathcal{N}(j)$ at the same level. We label the nodes in the scenario tree in lexicographic order with respect to the node IDs in the technology tree to establish the bijection $n \in \mathcal{N} \leftrightarrow (n_1, n_2, \ldots, n_{|\mathcal{J}|}) \in \mathcal{N}(1) \times \mathcal{N}(2) \times \cdots \mathcal{N}(|\mathcal{J}|)$. This construction can be best explained with an example: Let us consider the scenario tree in Figure 4.4, which is obtained from the technology trees in Figure 4.3. The labels of nodes 2, 3, 4, 5 in the scenario tree corresponds to the node ID triplets (2,2,2), (2,2,3), (2,3,2), (2,3,3) in the technology trees. In each triplet, the first, second, and third elements represent the node IDs of the DB, BEB, and HFCB technology trees, respectively.

The set $\mathcal{T}_n$ represents the set of time periods (years) corresponding to node n, where each year is divided into sub-periods (seasons).

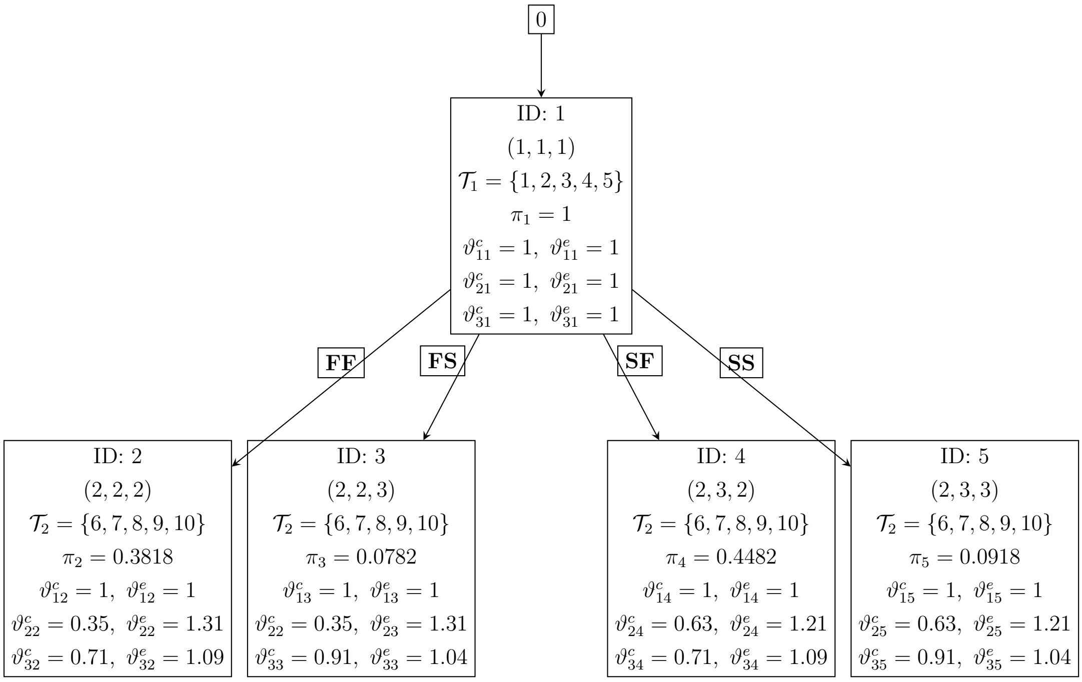


Figure 4.4 Scenario tree with two stages.

Finally, for each $n \in \mathcal{N}$ and $j \in \mathcal{J}$, we set $\pi_n = \prod_{j\in\mathcal{J}} \theta^p_{j,n_j}$ and $(\vartheta^c_{jn}, \vartheta^e_{jn}) = (\theta^c_{j,n_j}, \theta^e_{j,n_j})$. We note that in a general situation with $|\mathcal{J}|$ many technologies with respective branches of B_j over S stages, the scenario tree will contain $(\prod_{j=1}^{J} B_j)^{S-1}$ leaf nodes (or scenarios), which grows exponentially.

We are now ready to explain how the uncertain parameters are affected in each scenario. We use the abbreviation IC for investment cost, which does not change for DBs over the planning horizon.

For BEBs, technological advances affect the battery capacity (as we assume that the total bus weight remains unchanged) and investment cost. For a specific version with initial battery capacity of C_1, the battery capacity in node n becomes $C_n = C_1 \times \vartheta^e_{BEB,n}$. Then, we run Algorithm 1 to determine the new DSR with battery capacity C_n. Regarding the IC of a BEB of length L in node n with battery capacity C_n, we use the formula

$$\text{(4.1)} \qquad \mathrm{IC}_{\mathrm{BEB},n}(L, C_n) = \mathrm{IC}_{\mathrm{DB},1}(L) + \mathrm{CC} + (1 + \beta^{\omega/2})[\mathrm{PC} + \mathrm{BC} \times C_n]\vartheta^c_{\mathrm{BEB},n}.$$

Here, PC refers to the cost of other components of the electrified powertrain except the battery and CC stands for the charger cost.

For HFCBs, technological advances affect the investment and O&M costs. In particular, the IC of a HFCB of length L in node n is computed as $\mathrm{IC}_{\mathrm{HFCB},n}(L) = \mathrm{IC}_{\mathrm{DB},1}(L) + [\mathrm{IC}_{\mathrm{HFCB},1}(L) - \mathrm{IC}_{\mathrm{DB},1}(L)]\vartheta^{c}_{\mathrm{HFCB},n}$ and its consumption rate per distance (CR), which affects the unit energy cost, becomes $\mathrm{CR}_{\mathrm{HFCB},n} = \mathrm{CR}_{\mathrm{HFCB},1}/\vartheta^{e}_{\mathrm{HFCB},n}$.

5. CASE STUDY

This chapter presents our case study that focuses on the clean fleet transition in Istanbul public bus network. After we provide our computational setup in Section 5.1, we present the detailed results about our base case in Section 5.2. Then, we provide a thorough sensitivity analyses regarding some key parameters in our case study in Section 5.3. Finally, we compare our stochastic programming model with other approaches in Section 5.4.

5.1 Computational Setup

We conduct our computational experiments in the Python programming language using a 64-bit workstation with two Intel(R) Xeon(R) Gold 6248R CPU (3.00GHz) processors (256 GB RAM). Due to the large-scale nature of the multi-stage stochastic program (3.1), we relax the integrality restrictions and solve it as a linear program (LP) utilizing Gurobi 11. Since we cluster the routes into categories with a reasonably large demand, continuous variables provide an accurate approximation that can be rounded to obtain practical solutions. Specifically, after solving the LP relaxation, we round up all variables to the nearest integer and recalculate the objective function with these rounded values. In fact, in all cases considered, the difference between the optimal value of the LP relaxation, denoted by z_{LP} and the objective function value of the rounded solution, denoted by z_{round}, is at most 0.23%.

5.2 Base Case

In the `Base Case`, we obtain a dynamic strategic plan of Istanbul's transition to a clean fleet, spanning a planning horizon of 25 years (2025-2049) divided into five stages. We utilize the input data described in Chapter 4, and set the investment budget in million USD as $\gamma_t = \min\{50t, 250\}$ for $t = 1, \ldots, 25$. We also include yearly emission targets, reducing the yearly emission gradually to zero up to year 2049 at a linear rate starting from year 2035. We note that since we solve the problem from the perspective of the bus operator IETT, only tailpipe emissions are considered and the emissions related to electricity and hydrogen production, which IETT has no control over, are not included in our case study. We set the inflation rate $\zeta = 0.04$ and the nominal discount rate as $\beta_{nominal} = 0.05$. The initial fleet consists of 2,072 7-year-old, 2,817 11-year-old, 318 14-year-old, 635 16-year-old, and 711 18-year-old DBs. The maximum lifetime for buses with an initial age of 11 years or less is assumed to be 16 years, while buses that are 14 years or older are assumed to have a maximum lifetime of 20 years. The remaining lifetime of the initial buses is adjusted accordingly based on these assumptions. Since the fleet is quite old, we assume zero salvage value the existing buses. For newly purchased buses, the economic lifetime is set at 12 years for BEBs and HFCBs, and 15 years for diesel buses. The maximum average fleet age at the end of the planning horizon is capped at 9 years.

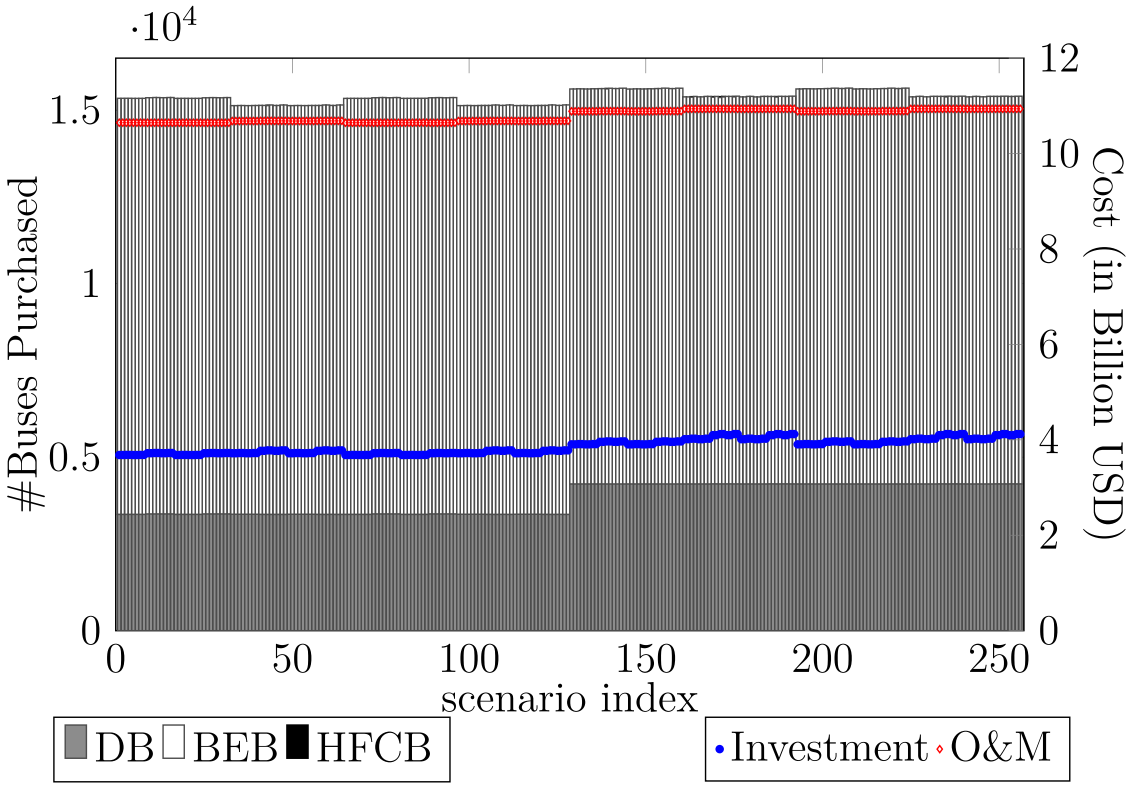


Figure 5.1 `Base Case` results. Buses purchased are reported with bars and the cost figures are reported with markers.

We consider three technology alternatives: DBs, BEBs and HFCBs. We assume that the cost of DBs do not change, but the cost and efficiency of BEBs and HFCBs improve as explained in Section 4.3 with respect to two clusters each. Therefore, we consider $(1 \times 2 \times 2)^{5-1} = 256$ scenarios in our multi-stage stochastic program. The resulting model contains more than 23 million variables and 3 million constraints. The CPU time is 5,435 seconds, and the expected objective values are $z_{\text{LP}} = 14.126$B USD and $z_{\text{round}} = 14.154$B USD, indicating only a 0.2% difference. For each scenario, we report the number of buses purchased of each technology type along with the total purchase and O&M costs over the planning horizon in Figure 5.1. Results indicate that the O&M costs are more than twice of the investments costs, which is expected for public buses heavily utilized in Istanbul. In addition, BEBs dominate across all scenarios, while HFCBs are purchased in small numbers and only in a few scenarios.

We also provide detailed results for four particular scenarios in Figure 5.2: i) Fast-Fast, ii) Fast-Slow, iii) Slow-Fast, iv) Slow-Slow. Here, Fast-Slow refers to the scenario where BEBs improves fast while HFCBs improve slow in each stage (the other three scenarios are defined accordingly). These four scenarios provide extreme cases and help us illustrate the effect of stochasticity in the dynamic strategic plans. As the initial fleet is quite old, most of the buses need to be retired within the first six years and the budget limitation is most influential in this time frame for all scenarios. We recall that heavily-utilized city buses typically have higher O&M cost in their economic lifetime compared to the initial investment cost. The purchase of BEBs, even in the first year (albeit in small quantities due to budget limitations), shows their advantage over DBs in saving O&M costs. This is especially true for routes where electrification can happen without needing many more buses, that is, routes with DSR values close to 1. We also observe that the fleet size peaks in year 15 for the Fast-Fast and Fast-Slow scenarios, and in year 17 for the Slow-Fast and Slow-Slow scenarios. In the following years, the fleet size slightly decreases due to the higher battery capacities of BEBs purchased in the final stage. The transition to ZEBs is almost complete by year 18 even under the Slow-Slow scenario. Therefore, the zero-emission target can be easily achieved and the adoption to BEBs is also economically justified due to their low O&M costs compared to DBs and HFCBs. Note that HFCBs are only purchased in the last few time periods of the planning horizon, and only in scenarios where the HFCB technology improves fast and BEB technology improves slowly. Even in the most favorable scenario for HFCBs, less than 0.4% of the fleet will be HFCBs in the end.

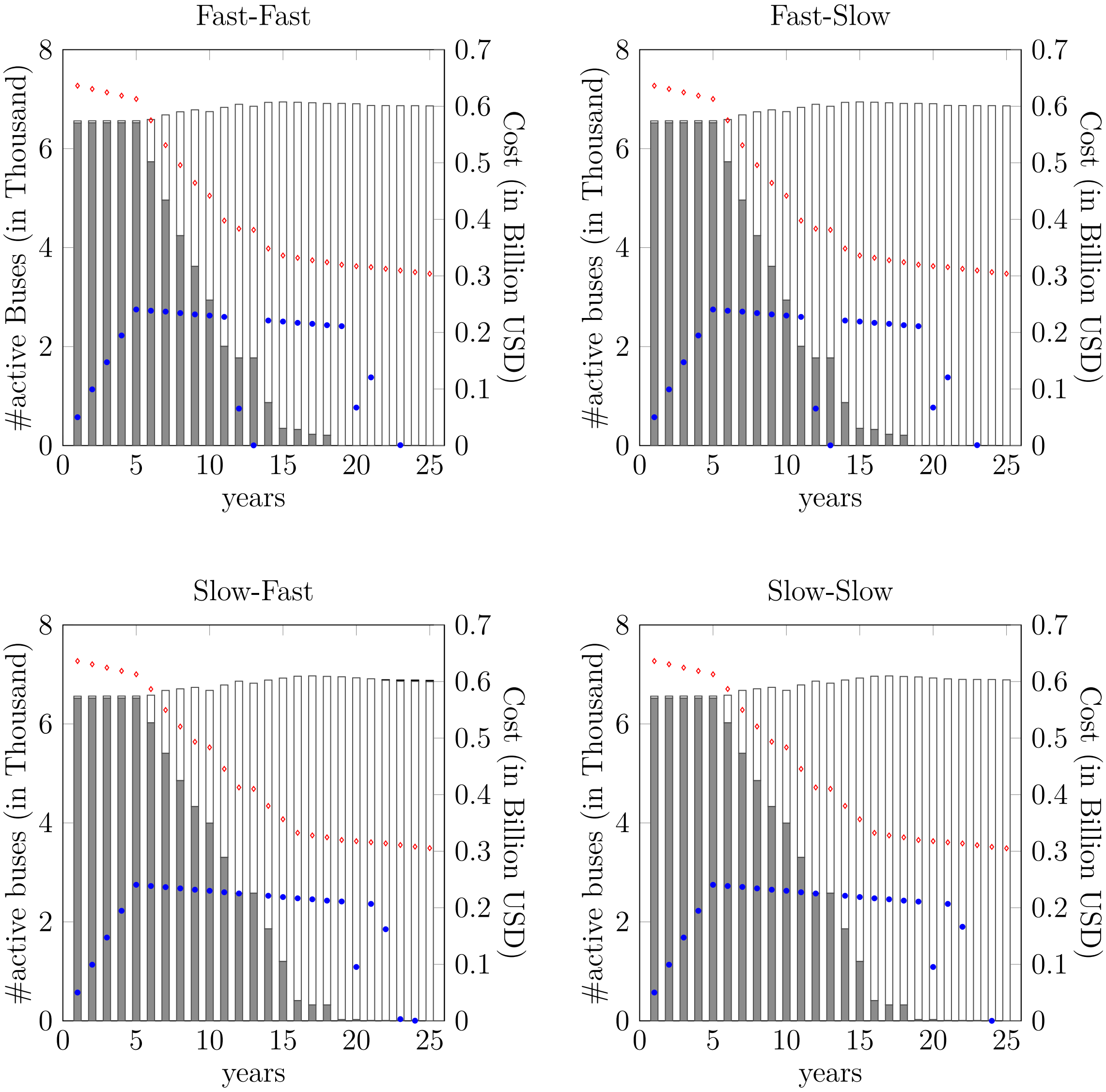


Figure 5.2 `Base Case` - four specific scenarios.

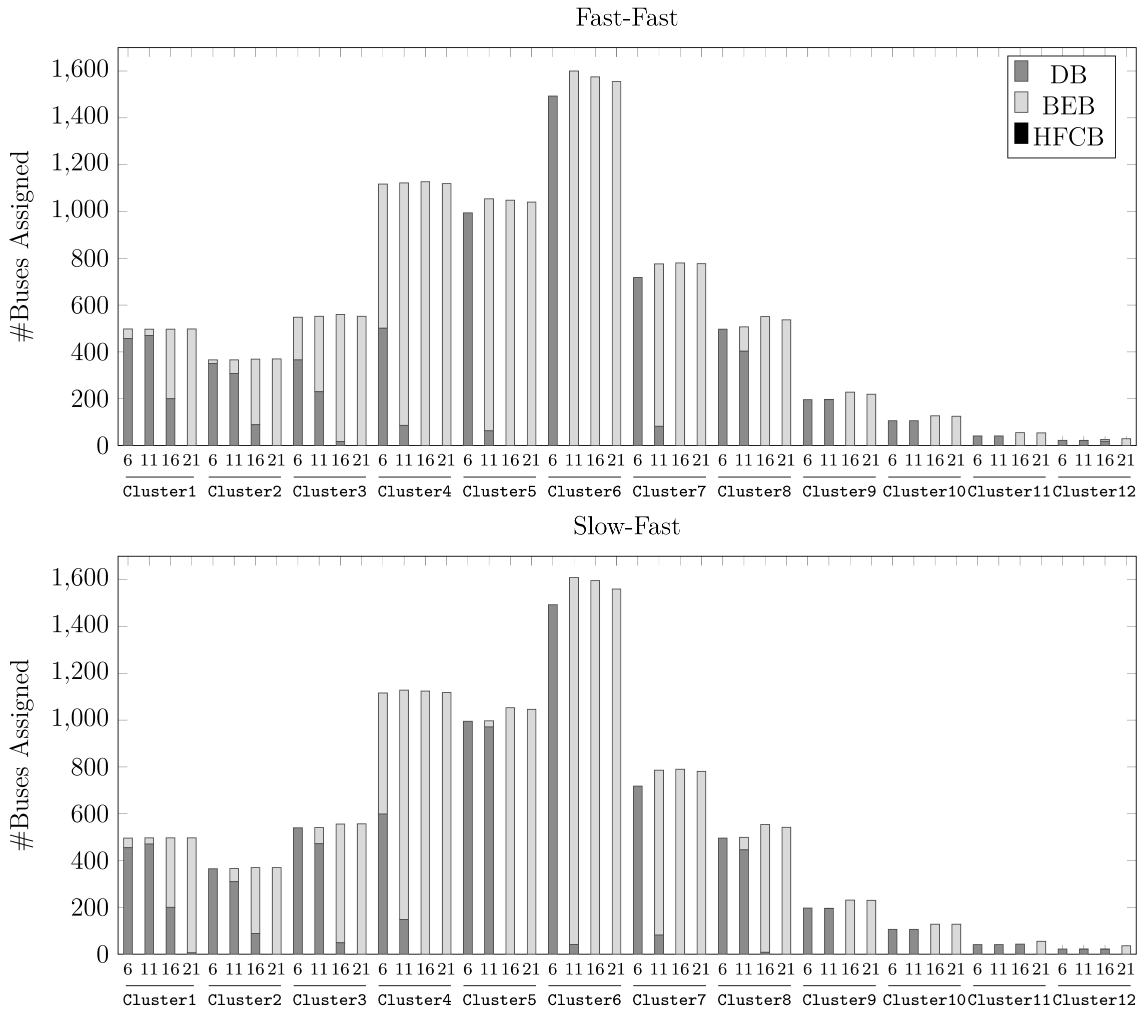


Figure 5.3 Fleet composition in years 6, 11, 16, 21 under different scenarios with respect to route clusters.

In Figure 5.3, we present the bus fleet composition for the first year of Stage 2 through Stage 5, corresponding to years 6, 11, 16, and 21, across two extreme scenarios: Fast-Fast and Slow-Fast. (The results of Fast-Slow and Slow-Slow are omitted, as they are almost identical to those of Fast-Fast and Slow-Fast, respectively). This figure shows the number of buses of each technology assigned to each cluster during the winter of those years. Recall that Cluster 1 has a DSR value of 1, meaning that it can be electrified with the same number of DBs, while larger cluster labels indicate smaller DSR values, which correspond to routes that may require additional BEBs compared to DBs. The results show that in all scenarios, the transition to BEBs does not begin for clusters 5 through 12 within the first 6 years of the planning period due to their lower DSR values. Additionally, the last four clusters are still using diesel buses during the first 11 years. Cluster 4 is electrified more in the first 6 years than the previous three clusters, likely due to greater savings in O&M costs and the higher age of the initial fleet corresponding to these clusters, among other factors.

We also observe that the few HFCBs purchased in the Slow-Fast scenario are bought in years 22-24 and are almost entirely assigned to cluster 12 to reduce the fleet size in that cluster.

Due to the recent population dynamics in Istanbul (TUIK, 2024), we have used a constant demand pattern. Nevertheless, to see the effects of a change in demand, we have performed an additional experiment in which we hypothetically increase the demand by randomly adding trips. It turns out that the transition strategy is quite similar in this case, which suggests that our conclusions remain valid. The detailed results can be found in the Appendix.

5.3 Sensitivity Analysis

We now present the results of our extensive sensitivity analyses, in which we change some key deterministic parameters of the multi-stage stochastic program that are exogenously determined such as the budget restrictions, emission targets and hydrogen prices. The choice of these parameters are also motivated by our findings from the `Base Case`: i) Budget restrictions are influencing the initial investment decisions, and forcing the model to choose DBs over BEBs due to the lower investment cost of the former despite the lower lifetime cost of the latter. ii) Emission targets are mostly redundant, which enables the model to make the best economical decisions that happen to address the environmental concerns as well. iii) HFCBs are quite expensive in terms of their O&M costs even without the consideration of potential infrastructure costs, which results in BEBs being the prominent choice for the transition.

These observations motivate us to explore the answers of the following questions: i) If IETT can spare more budget annually, how much cost benefit can be expected overall? ii) If even more strict emission targets are enforced, how much cost increase can be expected overall? ii) If hydrogen prices drop drastically, can HFCBs become the prominent ZEB choice and how much cost decrease can be expected overall?

To answer these questions, we re-run our multi-stage stochastic model three times for the following cases by keeping everything else the same:

i) `Relaxed Budget`: Budget is chosen 300 Million USD annually.

ii) `Strict Emissions`: Zero emission target is enforced in year 2040 with intermediate targets starting from year 2030.

iii) `Low Hydrogen Price`: Hydrogen price is set at 2 USD/kg.

In Table 5.1, we provide a summary of the sensitivity analysis conducted while the detailed results are available in the Appendix. We observe that "%Gap", defined as $100 \times \frac{z_{\text{round}} - z_{\text{LP}}}{z_{\text{round}}}$, is consistently small, which suggests that our rounding scheme is quite successful in the new cases as well. In addition, we also report "%Change", which is the percentage change of a new case with respect to the `Base Case` in terms of the objective function value of the rounded solution. As expected, in the `Relaxed Budget Case`, the change is negative, which indicates that an increased budget helps to obtain a more economical plan with 3.80% lower expected cost. Interestingly, the change in the `Strict Emission Case` is very small, which suggests that an even earlier transition to ZEBs can be achieved with increasing the overall cost marginally by 0.08%. Finally, the change in the expected total cost for the `Low Hydrogen Price Case` is also small (-0.17%), which shows the limited effect the hydrogen price has on the overall outcome.

Table 5.1 Summary results for different cases.

Case	**Time (sec)**	z_{LP}	z_{round}	**%Gap**	**%Change**
`Base`	5,435	14,126,110,527	14,154,103,467	0.20	-
`Relaxed Budget`	5,888	13,586,698,671	13,615,884,770	0.21	-3.80
`Strict Emission`	4,877	14,133,211,491	14,165,320,511	0.23	0.08
`Low Hydrogen Price`	6,133	14,099,073,373	14,129,697,437	0.22	-0.17

We also report the changes in the fleet decomposition and cost figures for the new cases with respect to the `Base Case` under four specific scenarios in Figure 5.4.

In the `Relaxed Budget Case`, we observe an increase in the number of BEBs purchased across all scenarios as BEBs are economically more advantageous than DBs in their economic lifetime despite their higher investment cost. This is clear from the moderate increase in the investment cost and the substantial decrease in the O&M cost, which is even more pronounced in the Slow-Fast and Slow-Slow scenarios.

In the `Strict Emission Case`, slightly more BEBs are being purchased, with the difference only being non-negligible in scenarios when BEBs improve slowly. This is due to the need to purchase BEBs between 2030 and 2040 to meet emission constraints, even in scenarios where improvements are slow. The small changes with this respect to the `Base Case` illustrate that BEBs are not only environmentally benefical but also cost effective.

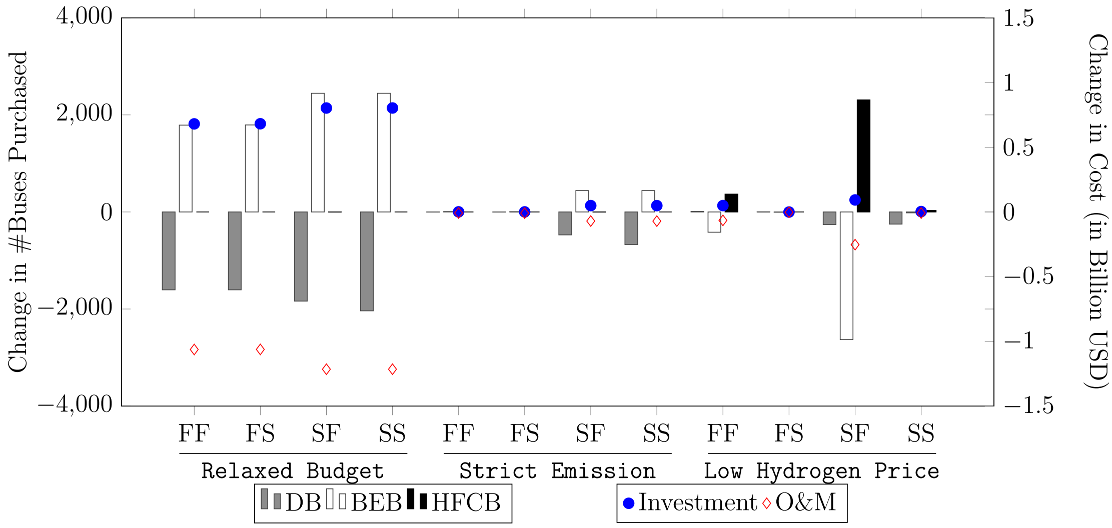


Figure 5.4 Changes in bus purchases (shown with bars) and cost values (shown with markers) compared to the `Base Case` for four specific scenarios in different cases. FF, FS, SF, SS are respectively the abbreviations of Fast-Fast, Fast-Slow, Slow-Fast, Slow-Slow scenarios as described earlier.

In the `Low Hydrogen Price Case`, results indicate that the number of HFCBs purchased increases in most scenarios. In particular, for the four specific scenarios, HFCB purchases increase in three of them, but remain at zero in the Fast-Slow scenario. We also observe that HFCB purchases begin in year 6 in the Slow-Fast scenario, where HFCBs are expected to make up 24.4% of the fleet by the final time period. Nevertheless, as the expected total cost reduction is very small overall, this case suggests that HFCBs will not be dominantly more preferable over BEBs, even if we ignore potential infrastructure costs and potential difficulties regarding hydrogen supply chain.

5.4 Model Comparison

5.4.1 Comparison with a Deterministic Model

To analyze the effect of stochasticity, we solve a deterministic version of our problem and compare its solution with that of the multi-stage stochastic program. In the deterministic model, the technology improvements described in Section 4.3 are represented as a single scenario, reflecting the average of all historical advancements. Specifically, the anticipated cost multipliers for BEBs and HFCBs are 0.48

and 0.74, respectively while the efficiency multipliers are 1.26 and 1.08, respectively. The model solves in 6.4 seconds, and the objective function values are obtained as $z_{\text{LP}} = 13.233$B USD and $z_{\text{round}} = 13.256$B USD. We observe that the deterministic problem's z_{round} value is 0.91B USD (6.43%) lower than that of the stochastic program. Although these models and their objective functions are different, this decrease indicates that the solution of deterministic problem cannot be feasible for the stochastic program and we quantify these infeasibilities as described below.

First, we apply the solution of the deterministic problem to each scenario of the stochastic program. To do this, we adjust the battery capacities of BEBs in each scenario based on the capacities from the deterministic solution. However, since energy density improvements vary across scenarios, we need to adjust the bus weights accordingly to reflect the expected improvements in each stochastic scenario. Then, using equation 4.1, we calculate the BEB investment costs, where C_n (the battery capacity in node n) comes from the deterministic solution, and $\vartheta^{\text{c}}_{\text{BEB},n}$ (the efficiency improvement) relates to each specific scenario. We observe that the deterministic solution violates the budget constraints in 160 out of 256 scenarios of the stochastic program in at least one time period by more than 1%. Considering the probabilities of these scenarios, this means that there is a 67.41% probability that the deterministic solution will not be feasible due to insufficient budget. Note that these budget violations are even underestimated because, in scenarios where energy density improves more slowly than in the deterministic case, heavier batteries are required, necessitating more buses to meet demand.

Table 5.2 details the budget violations of the deterministic solution in the stochastic program. Since no HFCBs are purchased in the deterministic problem, it suffices to consider a reduced scenario tree with $2^{5-1} = 16$ scenarios, in which only BEB improvements are considered. In particular, scenarios in Table 5.2 represent BEB improvements from stage 2 to stage 5 (e.g., FSSF refers to fast improvement in stage 2, slow in stages 3 and 4, and fast again in stage 5). The table shows the percentage of budget violations under different scenarios, and for each year within the stage. For example, the numbers 6.11, 6.76, 6.17, 4.87, 5.15 correspond to the percentage budget violations in years 6, 7, 8, 9, 10 respectively, and under the eight specified BEB improvement scenarios. The observed infeasibilities highlight the importance of stochastic modelling and dynamic planning in strategic decision making. By accounting for uncertainty in technology improvements, the stochastic model avoids the infeasibilities that arise when applying the deterministic solution, ensuring a more robust and feasible plan.

Table 5.2 Percent violations of budget constraints in different stages under different scenarios. A non-empty cell gives the yearly violations in that stage while the symbol '–' indicates that there is no violation in the corresponding year. An empty cell indicates that there is no violation in that stage.

<table>
<tr><td>Stage 2</td><td colspan="8"></td><td colspan="8">6.11,6.76,6.17,4.87,5.15</td></tr>
<tr><td>Stage 3</td><td colspan="4"></td><td colspan="4"></td><td colspan="4"></td><td colspan="4">11.96,11.98,–,11.43,9.39</td></tr>
<tr><td>Stage 4</td><td colspan="2"></td><td colspan="2"></td><td colspan="2"></td><td colspan="2">1.25,1.42,1.44,1.40,–</td><td colspan="2"></td><td colspan="2">1.25,1.42,1.44,1.40,–</td><td colspan="2">1.25,1.42,1.44,1.40,–</td><td colspan="2">11.32,12.23,12.36,12.18,–</td></tr>
<tr><td>Stage 5</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>2.60,–,–,–,–</td><td></td><td></td><td></td><td>2.60,–,–,–,–</td><td></td><td>2.60,–,–,–,–</td><td>2.60,–,–,–,–</td><td>9.32,–,–,–,–</td></tr>
<tr><td></td><td>FFFF</td><td>FFFS</td><td>FFSF</td><td>FFSS</td><td>FSFF</td><td>FSFS</td><td>FSSF</td><td>FSSS</td><td>SFFF</td><td>SFFS</td><td>SFSF</td><td>SFSS</td><td>SSFF</td><td>SSFS</td><td>SSSF</td><td>SSSS</td></tr>
</table>

5.4.2 Comparison with Other Stochastic Models

To better understand the impact of scenarios on the optimal solution, we extend the scenario tree and solve the stochastic model using two extended versions. In the first version called the `3-by-2 Case`, we include 3 branches for BEB improvements at each stage (corresponding to Figure 4.1c) and 2 branches for HFCBs. The second version called the `2-by-3 Case` maintains 2 branches for BEBs and extends the number of HFCB branches to 3 (corresponding to Figure 4.2c). In both versions, the number of scenarios increases to $(1 \times 2 \times 3)^{5-1} = 1296$, making the problem size significantly larger complex. To manage this, we simplify certain assignment decisions. Specifically, for route-bus length pairs with higher demand in the winter schedule, assignment variables for other seasons are excluded. Instead, we assume that buses assigned to a cluster remain there across all seasons, with their usage adjusted based on seasonal demand, to account for lower O&M costs during other seasons. The detailed results are reported in the Appendix.

We observe that in both extended cases the overall transition plan is similar to the `Base Case` as BEBs are still the dominant choice. However, in the Fast-Fast and Fast-Slow scenarios of the `3-by-2 Case`, the transition completes earlier, as the Fast improvement branch of BEBs is faster in the `3-by-2 Case` than the `Base Case`. We also observe that HFCB purchases are almost identical in the `3-by-2 Case` to the `Base Case`, meaning only a few buses being purchased in the final stage and under the Slow-Fast scenario, out of the 4 extreme scenarios. This is because the Slow improvement branch of BEBs in the `3-by-2 Case` is not much different than that of the Base Case. The `2-by-3 Case` results are nearly identical to the `Base Case`, with a negligible change in the objective function value.

6. CONCLUSION

In this study, we propose a multi-stage stochastic program for the bus fleet replacement problem where we consider the uncertainties in the technology advancements and cost improvements of different bus technologies. We present a forecasting approach where we examine historical cost and efficiency trends of different technology options and compute the improvement ratios over the years. These ratios are then clustered into different groups which are provided to the multi-stage stochastic program as scenarios. We use our model to plan the transition of municipal bus network in Istanbul to clean alternatives (BEBs and HFCBs) over a planning horizon of 25 years with a zero-emission target in 2050. In our plan, we consider the changes in the energy consumption of BEBs on different routes and at different seasons, and we ensure operational feasibility by finding the diesel-electric replacement ratios and recharge scheduling for FC electric buses. We perform sensitivity analyses to test the effect of certain exogenously determined parameters and inputs on our results. We also compare our stochastic programming approach with a deterministic model, and show its advantage in providing feasible dynamic strategic transition plans.

Our results from the multi-stage stochastic program indicate that BEBs are viable alternatives to replace DBs to achieve zero emission bus fleet goals. BEBs can already satisfy the demand in most of the routes in Istanbul without the need to plan new bus lines or timetables even at today's technology level. Their lower O&M cost compared to DBs make them advantageous in the long term across all scenarios we implemented. Although DBs are needed to be purchased initially due to the old age of the fleet and higher investment costs of BEBs, as costs improve BEBs can replace all DBs and transition to an all-electric fleet can be completed in less than 20 years in most scenarios. The advantages of BEBs also manifest themselves in the sensitivity analyses we performed. When the available budget is higher, more BEBs are purchased accross all scenarios, proving that once initial investment barrier is overcome, BEBs are better alternatives to DBs over their lifetime. We also observe that, under tighter emission constraints the number of BEBs increase only negligibly under most scenarios, showing BEBs are not only environmentally beneficial but also cost effective. We acknowledge that other adoption challenges such as potential need for grid investments, recharging scheduling and training of the personnel can pose certain barriers and slow down the transition in practice.

HFCBs do not prove to be preferable over BEBs across our scenarios- even under the most favorable scenario, less than 0.4% of the fleet consists of HFCBs. Higher investment and operational costs both play a role in this result. When the energy costs are decreased by one fifth, the fleet can consist of up to 24% of HFCBs in the most favorable scenario but HFCBs still cannot be dominant due to their higher initial costs.

There are some limitations of our work that should be considered while interpreting our results. In this study, we assumed that the municipality is not responsible for building hydrogen transmission and storage infrastructure, or potential grid investments necessary for increased electricity demand. In a setting where the municipality has to invest in infrastructure, transition to cleaner alternatives might be slower. In addition, our results are based on scenarios obtained using limited historical HFCB cost and technological development trends compared to BEBs. According to these trends, even slow improvement in BEBs is faster than in HFCBs. However, our scenarios assume constant improvements based on past data, and HFCBs are still at their early adoption stages being produced at limited numbers. It is possible that BEBs will reach a saturation in improvement sooner than HFCBs, which might change the results in favor of HFCBs in the future.

While this study focuses on strategical planning of the transition to zero emission buses, it can be enhanced by adding more tactical and operational aspects. For example, bus-to-route simulator might be improved by including recharge and maintenance scheduling optimization as well as battery degradation aspects. In our study, we assume each bus is changed with a bus of the same length, trip schedules do not change with transition and chargers are available at the last stop of every route when needed. Each of these assumptions pose an optimization problem by themselves: optimal bus size selection and assignment problem, optimizing trip schedules and charge location optimization. Our future work will focus on these problems and investigate how to integrate them into our model.

Finally, we will also investigate how to solve the large-scale multi-stage stochastic program more efficiently. This is especially important if one needs to include more technology options and construct larger technology trees that might provide a more realistic case study, albeit with a significantly larger scenario tree. In this case, obtaining structural results to systematically eliminate variables and constraints, and developing decomposition methods may prove to be necessary.

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APPENDIX A: ENERGY REQUIREMENT CALCULATION

A.1 Determining the Segment Duration

To find τ_1 and τ_2, we can solve an optimization problem that minimizes the time spent within a segment of length d and a fixed acceleration a satisfying the condition that $V(\tau) \leq V_{\max}$ and

$$P_w(\tau) = \Big(mg\sin\alpha + f_r\, mg\cos\alpha + \tfrac{1}{2}\rho_{\text{air}} C_D A_f v(\tau)^2 + m_{\text{eq}} a(\tau)\Big)\, v(\tau) \\ \leq \min\Big\{P_{\max},\ \kappa V(\tau)\Big\}.$$

for $\tau \in [0, \tau_1 + \tau_2]$. To simplify, let us rewrite $P_w(\tau)$ as

$$P_w(\tau) = \Big(A + Bv(\tau)^2 + Ca(\tau)\Big)\, v(\tau).$$

Since the air resistance is much smaller than the other components (that is, $Bv(\tau)^2 \ll |A + Ca(\tau)|$ for the bus specifications and speed profiles we are interested in), we can formulate this optimization problem as follows when $\alpha > 0$ (for $\alpha < 0$, the power constraint is redundant):

$$\min\{\tau_1 + \tau_2 : a\tau_1 \leq V_{\max},\ a\tau_1\tau_2 = d,\ \tau_2 \geq \tau_1,\ P_w(\tau_1) \leq \min\{P_{\max}, \kappa a\tau_1)\}\}.$$

We can eliminate τ_2 by substituting $\frac{d}{a\tau_1}$:

$$\min\left\{\tau_1 + \frac{d}{a\tau_1} : a\tau_1 \leq V_{\max},\ \frac{d}{a\tau_1} \geq \tau_1,\ P_w(\tau_1) \leq P_{\max}, \tau \leq \sqrt{\frac{\kappa - A - Ca}{Ba^2}}\right\}.$$

Note that $\tau_1 + \frac{d}{a\tau_1}$ is a convex function with its minimizer at $\tau_1 = \sqrt{\frac{d}{a}}$. Since the cubic polynomial $P_w(\tau_1)$ is increasing under our assumptions, there exists a single root for $P_w(\tau_1) = P_{\max}$, which we denote by τ_R (note that we can search for that root in the interval $[0, \frac{V_{\max}}{a}]$). Finally, we conclude that the optimal solution is

$$\tau_1^* = \min\left\{\sqrt{\frac{d}{a}}, \frac{V_{\max}}{a}, \sqrt{\frac{\kappa - A - Ca}{Ba^2}}, \tau_R\right\} \text{ and } \tau_2^* = \frac{d}{a\tau_1^*}.$$

A.2 Calculating the Energy Consumption for BEBs

- In the acceleration phase, that is $\tau \in [0, \tau_1]$, we have $a(\tau) = a$, $v(\tau) = a\tau$, and we are interested in the following integral:

$$\int_0^{\tau_1} P_{\mathrm{w}}(\tau)d\tau = \int_0^{\tau_1} (A + Ba^2\delta^2 + Ca)a\tau d\tau.$$

  - If $A + Ca \geq 0$, we have

$$\begin{aligned}\int_0^{\tau_1} P_{\mathrm{bat}}(\tau)d\tau &= \frac{1}{\eta_t\eta_m}\int_0^{\tau_1} P_w(\tau)d\tau = \frac{1}{\eta_t\eta_m}\int_0^{\tau_1}\left(A + B(a\tau)^2 + Ca\right)(a\tau)d\tau \\ &= \frac{1}{\eta_t\eta_m}\left[\frac{1}{2}(A + Ca)a\tau_1^2 + \frac{1}{4}Ba^3\tau_1^4\right].\end{aligned}$$

  - If $A + Ca < 0$ and $\bar{\tau} := \sqrt{\frac{-(A+Ca)}{Ba^2}} \geq \tau_1$, we have

$$\int_0^{\tau_1} P_{\mathrm{bat}}(\tau)d\tau = \eta_t\eta_m\eta_{rb}\int_0^{\tau_1} P_w(\tau)d\tau = \eta_t\eta_m\eta_{rb}\left[\frac{1}{2}(A + Ca)a\tau_1^2 + \frac{1}{4}Ba^3\tau_1^4\right].$$

  - If $A + Ca < 0$ and $\bar{\tau} := \sqrt{\frac{-(A+Ca)}{Ba^2}} < \tau_1$, we have

$$\begin{aligned}\int_0^{\tau_1} P_{\mathrm{bat}}(\tau)\,d\tau &= \eta_t\eta_m\eta_{rb}\int_0^{\bar{\tau}} (A + Ba^2\delta^2 + Ca)a\delta\,d\delta \\ &\quad + \frac{1}{\eta_t\eta_m}\int_{\bar{\tau}}^{\tau_1} (A + Ba^2\delta^2 + Ca)a\delta\,d\delta \\ &= \eta_t\eta_m\eta_{rb}\Big[\tfrac{1}{2}(A + Ca)a\bar{\tau}^2 + \tfrac{1}{4}Ba^3\bar{\tau}^4\Big] \\ &\quad + \frac{1}{\eta_t\eta_m}\Big[\tfrac{1}{2}(A + Ca)a(\tau_1^2 - \bar{\tau}^2) + \tfrac{1}{4}Ba^3(\tau_1^4 - \bar{\tau}^4)\Big].\end{aligned}$$

- In the constant speed phase, that is $\tau \in [\tau_1, \tau_2]$, we have $a(\tau) = 0$ and $v(\tau) =$

$a\tau_1$, and we are interested in the following integral:

$$\int_{\tau_1}^{\tau_2} P_w(\tau)d\tau = \int_{\tau_1}^{\tau_2} \left(A + B(a\tau_1)^2\right)(a\tau_1)d\tau = \left(A + B(a\tau_1)^2\right)(a\tau_1)(\tau_2 - \tau_1) =: \mathcal{C}.$$

– If $\mathcal{C} \geq 0$, we have

$$\int_{\tau_1}^{\tau_2} P_{\text{bat}}(\tau)d\tau = \frac{1}{\eta_t\eta_m}\int_{\tau_1}^{\tau_2} P_w(\tau)d\tau = \frac{1}{\eta_t\eta_m}\mathcal{C}.$$

– If $\mathcal{C} < 0$, we have

$$\int_{\tau_1}^{\tau_2} P_{\text{bat}}(\tau)d\tau = \eta_t\eta_m\eta_{rb}\int_{\tau_1}^{\tau_2} P_w(\tau)d\tau = \eta_t\eta_m\eta_{rb}\mathcal{C}.$$

- In the deceleration phase, that is $\tau \in [\tau_2, \tau_1 + \tau_2]$, we have $a(\tau) = -a$ and $v(\tau) = a(\tau_1 + \tau_2 - t)$. Let us first apply change of variables $\delta = \tau_1 + \tau_2 - \tau$ so that we are interested in the following integral:

$$\int_{\tau_2}^{\tau_1+\tau_2} P_{\text{w}}(\tau)d\tau = \int_0^{\tau_1} P_{\text{w}}(\tau_1 + \tau_2 - \delta)d\delta = \int_0^{\tau_1}(A + Ba^2\delta^2 - Ca)a\delta d\delta.$$

– If $A - Ca \geq 0$, we have

$$\begin{aligned}\int_{\tau_2}^{\tau_1+\tau_2} P_{\text{bat}}(\tau)\,d\tau &= \frac{1}{\eta_t\eta_m}\int_0^{\tau_1}(A + Ba^2\delta^2 - Ca)a\delta\,d\delta \\ &= \frac{1}{\eta_t\eta_m}\Big[\tfrac{1}{2}(A - Ca)a\tau_1^2 + \tfrac{1}{4}Ba^3\tau_1^4\Big].\end{aligned}$$

– If $A - Ca < 0$ and $\bar{\delta} = \sqrt{\dfrac{Ca - A}{Ba^2}} \geq \tau_1$, we have

$$\begin{aligned}\int_{\tau_2}^{\tau_1+\tau_2} P_{\text{bat}}(\tau)\,d\tau &= \eta_t\eta_m\eta_{rb}\int_0^{\tau_1}(A + Ba^2\delta^2 - Ca)a\delta\,d\delta \\ &= \eta_t\eta_m\eta_{rb}\Big[\tfrac{1}{2}(A - Ca)a\tau_1^2 + \tfrac{1}{4}Ba^3\tau_1^4\Big].\end{aligned}$$

– If $A - Ca < 0$ and $\bar{\delta} = \sqrt{\dfrac{Ca - A}{Ba^2}} < \tau_1$, we have

$$\begin{aligned}\int_{\tau_2}^{\tau_1+\tau_2} P_{\text{bat}}(\tau)\,d\tau &= \eta_t\eta_m\eta_{rb}\int_0^{\bar{\delta}} (A + Ba^2\delta^2 - Ca)a\delta\,d\delta \\ &\quad + \frac{1}{\eta_t\eta_m}\int_{\bar{\delta}}^{\tau_1} (A + Ba^2\delta^2 - Ca)a\delta\,d\delta \\ &= \eta_t\eta_m\eta_{rb}\Big[\tfrac{1}{2}(A - Ca)a\bar{\delta}^2 + \tfrac{1}{4}Ba^3\bar{\delta}^4\Big] \\ &\quad + \frac{1}{\eta_t\eta_m}\Big[\tfrac{1}{2}(A - Ca)a(\tau_1^2 - \bar{\delta}^2) + \tfrac{1}{4}Ba^3(\tau_1^4 - \bar{\delta}^4)\Big].\end{aligned}$$

For the energy requirement calculations, we use the parameters listed in Table A.1 for BEBs. Vehicle mass m includes the body mass m_{body} and the energy capacity multiplied with the unit battery mass m_{bat}.

Table A.1 List of parameters for traction power and battery power calculations (acceleration and vehicle body mass are given for 8, 10, 12, 18 m bus groups, respectively).

Parameter	Value	Parameter	Value
f_r	0.01	ρ_{air}	1.225 kg/m^3
C_D	0.7	g	9.81 m/s^2
A_f	$0.85 \times 3.25 \times 2.55 = 7.04$m^2	η_t	0.9
η_m	0.9	η_{rb}	0.25
m_{body}	9.5, 15, 16, 25 tonnes	m_{bat}	5 kg/kWh
m_{eq}	$1.1 \times m$	a	2.1, 1.8, 1.7, 1.5 m/s^2

APPENDIX B: DATA

B.1 IETT Data Details

Here is a snapshot of the “Trip Schedule" dataset:

Day	Route Code	Route Name	Trip ID	Scheduled Start Time	Planned Km	Vehicle Depot	Vehicle Length Group (m)
15.03.2023	129T	BOSTANCI - TAKSİM	129T_D_D0	15.03.2023 08:00:00	19.37409	ÖHO	11-14
15.03.2023	129T	BOSTANCI - TAKSİM	129T_G_D0	15.03.2023 09:30:00	22.8153	ÖHO	11-14
15.03.2023	129T	BOSTANCI - TAKSİM	129T_D_D0	15.03.2023 11:00:00	19.37409	ÖHO	11-14
15.03.2023	129T	BOSTANCI - TAKSİM	129T_G_D0	15.03.2023 13:00:00	22.8153	ÖHO	11-14

Figure B.1 Snapshot of the “Trip Schedule" dataset.

Summary statistics of the “Trip Schedule" dataset are provided in Tables B.1 and B.2 .

Table B.1 Trip-schedule summary for August 3 2023 (summer).

Bus Length (m)	**Planned Services**	**Planned Distance (km)**	**Assigned Routes**
6.5–8	2 898	63 525	38
8–9	277	4 320	14
10–11	76	3 086	8
11–14	35 761	823 868	738
11–14 (NG)	1 464	26 448	129
14–19	7 727	274 523	79
Total	**48 203**	**1 192 684**	**820**

Table B.2 Trip-schedule summary for March 15 2023 (winter).

Bus Length (m)	Planned Services	Planned Distance (km)	Assigned Routes
6.5–8	2 948	61 200	37
8–9	275	4 308	14
10–11	64	2 635	6
11–14	36 578	853 222	736
11–14 (NG)	1 554	30 263	145
14–19	9 130	317 813	98
Total	**50 549**	**1 269 441**	**819**

Here is a snapshot of the “Stop Sequence with Coordinates" dataset:

Route Code	Trip ID	Stop Name	Stop ID	Stop Type	X Coordinate	Y Coordinate	Sequence	Haversine Distance (km)	Elevation (m)
129T	129T_D_D0	GÜMÜŞSUYU PERON	301421	WALLMODERN	28.98936272	41.03986358	1	-	76
129T	129T_D_D0	GÜMÜŞSUYU	117382	İETTBAYRAK	28.991199	41.039178	2	0.171842796	51
129T	129T_D_D0	MİMAR SİNAN ÜNİVERSİTESİ	184932	İETTBAYRAK	29.00111964	41.04067353	3	0.848490852	9
129T	129T_D_D0	DENİZ MÜZESİ	184091	WALLMODERN	29.00654803	41.04190763	4	0.475496587	11

Figure B.2 Snapshot of the “Stop Sequence with Coordinates” dataset.

B.2 Technological Change

B.2.1 BEB Technological Change

Table B.3 presents historical data on BEB energy density and cost, while Table B.4 shows the clustered scenarios for BEB technology advances.

B.2.2 HFCB Technological Change

Tables B.5 and B.6 present, respectively, the historical data on the efficiency and costs of HFCBs and the clustered scenarios for HFCB technology advancements.

Table B.3 Technological change for BEBs over the years (energy density is given in Wh/kg and battery cell cost is given wrt 2023 USD/kWh).

Year	Energy Density	Cost	Year	Energy Density	Cost	Year	Energy Density	Cost
1991	98.20	8805.20	2002	188.18	1327.70	2013	243.23	472.73
1992	102.75	7166.22	2003	193.37	1014.27	2014	251.54	409.52
1993	107.86	5756.38	2004	209.99	909.97	2015	248.43	280.86
1994	112.98	6451.60	2005	202.72	788.02	2016	259.85	235.02
1995	118.66	6068.66	2006	207.92	675.05	2017	276.47	170.31
1996	126.62	5151.87	2007	222.46	644.22	2018	293.09	142.60
1997	130.59	4398.27	2008	218.30	673.49	2019	313.87	119.58
1998	144.80	3541.91	2009	222.46	580.73	2020	334.64	111.57
1999	156.37	2741.66	2010	230.77	533.49	2021	389.70	107.44
2000	160.13	2576.53	2011	238.04	499.68	2022	444.75	119.23
2001	179.87	1832.35	2012	243.23	507.12	2023	499.80	100.63

Table B.4 Clustering results for BEBs.

Clusters	Cluster Probability	Energy Density Improvement Rate	Cost Improvement Rate	Energy Density Change	Cost Change
2 Clusters	**F** (0.46)	0.27	1.05	1.31	0.35
	S (0.54)	0.19	0.45	1.21	0.63
3 Clusters	**F** (0.32)	0.25	1.14	1.28	0.32
	M (0.25)	0.24	0.79	1.27	0.45
	S (0.429)	0.21	0.39	1.24	0.68

Table B.5 Technological change for HFCBs over the years (fuel cell system cost is given wrt 2016 USD/kW).

Year	Efficiency	Cost	Year	Efficiency	Cost	Year	Efficiency	Cost
2010		175	2015		99	2020	0.57	76
2011		142	2016		99	2021	0.57	
2012	0.50	122	2017	0.55	78	2022		71
2013	0.50	119	2018		79	2023	0.57	
2014		107	2019		79	2024	0.60	

Table B.6 Clustering results for HFCBs.

Clusters	Cluster Probability	Efficiency Improvement Rate	Cost Improvement Rate	Efficiency Change	Cost Change
2 Clusters	**F** (0.83)	0.09	0.35	1.09	0.71
	S (0.17)	0.04	0.09	1.04	0.91
3 Clusters	**F** (0.33)	0.10	0.43	1.11	0.65
	M (0.50)	0.08	0.29	1.08	0.75
	S (0.17)	0.04	0.09	1.04	0.91

B.3 Scenario Table

Table B.7 shows the technological improvements across different stages of each scenario, along with the scenario's probability (in percent). The columns labeled S2, S3, S4, and S5 refer to stages 2, 3, 4, and 5, respectively. In each stage, the first letter represents the BEB improvement, and the second letter refers to the HFCB improvement. For example, "FS" means that BEBs improve fast, while HFCBs improve slow.

ID	S2	S3	S4	S5	Prob. (%)	ID	S2	S3	S4	S5	Prob. (%)	ID	S2	S3	S4	S5	Prob. (%)	ID	S2	S3	S4	S5	Prob. (%)
1	FF	FF	FF	FF	2.12493	65	FS	FF	FF	FF	0.43523	129	SF	FF	FF	FF	2.49448	193	SS	FF	FF	FF	0.51092
2	FF	FF	FF	FS	0.43523	66	FS	FF	FF	FS	0.08914	130	SF	FF	FF	FS	0.51092	194	SS	FF	FF	FS	0.10465
3	FF	FF	FF	SF	2.49448	67	FS	FF	FF	SF	0.51092	131	SF	FF	FF	SF	2.92830	195	SS	FF	FF	SF	0.59977
4	FF	FF	FF	SS	0.51092	68	FS	FF	FF	SS	0.10465	132	SF	FF	FF	SS	0.59977	196	SS	FF	FF	SS	0.12284
5	FF	FF	FS	FF	0.43523	69	FS	FF	FS	FF	0.08914	133	SF	FF	FS	FF	0.51092	197	SS	FF	FS	FF	0.10465
6	FF	FF	FS	FS	0.08914	70	FS	FF	FS	FS	0.01826	134	SF	FF	FS	FS	0.10465	198	SS	FF	FS	FS	0.02143
7	FF	FF	FS	SF	0.51092	71	FS	FF	FS	SF	0.10465	135	SF	FF	FS	SF	0.59977	199	SS	FF	FS	SF	0.12284
8	FF	FF	FS	SS	0.10465	72	FS	FF	FS	SS	0.02143	136	SF	FF	FS	SS	0.12284	200	SS	FF	FS	SS	0.02516
9	FF	FF	SF	FF	2.49448	73	FS	FF	SF	FF	0.51092	137	SF	FF	SF	FF	2.92830	201	SS	FF	SF	FF	0.59977
10	FF	FF	SF	FS	0.51092	74	FS	FF	SF	FS	0.10465	138	SF	FF	SF	FS	0.59977	202	SS	FF	SF	FS	0.12284
11	FF	FF	SF	SF	2.92830	75	FS	FF	SF	SF	0.59977	139	SF	FF	SF	SF	3.43757	203	SS	FF	SF	SF	0.70408
12	FF	FF	SF	SS	0.59977	76	FS	FF	SF	SS	0.12284	140	SF	FF	SF	SS	0.70408	204	SS	FF	SF	SS	0.14421
13	FF	FF	SS	FF	0.51092	77	FS	FF	SS	FF	0.10465	141	SF	FF	SS	FF	0.59977	205	SS	FF	SS	FF	0.12284
14	FF	FF	SS	FS	0.10465	78	FS	FF	SS	FS	0.02143	142	SF	FF	SS	FS	0.12284	206	SS	FF	SS	FS	0.02516
15	FF	FF	SS	SF	0.59977	79	FS	FF	SS	SF	0.12284	143	SF	FF	SS	SF	0.70408	207	SS	FF	SS	SF	0.14421
16	FF	FF	SS	SS	0.12284	80	FS	FF	SS	SS	0.02516	144	SF	FF	SS	SS	0.14421	208	SS	FF	SS	SS	0.02954
17	FF	FS	FF	FF	0.43523	81	FS	FS	FF	FF	0.08914	145	SF	FS	FF	FF	0.51092	209	SS	FS	FF	FF	0.10465
18	FF	FS	FF	FS	0.08914	82	FS	FS	FF	FS	0.01826	146	SF	FS	FF	FS	0.10465	210	SS	FS	FF	FS	0.02143
19	FF	FS	FF	SF	0.51092	83	FS	FS	FF	SF	0.10465	147	SF	FS	FF	SF	0.59977	211	SS	FS	FF	SF	0.12284
20	FF	FS	FF	SS	0.10465	84	FS	FS	FF	SS	0.02143	148	SF	FS	FF	SS	0.12284	212	SS	FS	FF	SS	0.02516
21	FF	FS	FS	FF	0.08914	85	FS	FS	FS	FF	0.01826	149	SF	FS	FS	FF	0.10465	213	SS	FS	FS	FF	0.02143
22	FF	FS	FS	FS	0.01826	86	FS	FS	FS	FS	0.00374	150	SF	FS	FS	FS	0.02143	214	SS	FS	FS	FS	0.00439
23	FF	FS	FS	SF	0.10465	87	FS	FS	FS	SF	0.02143	151	SF	FS	FS	SF	0.12284	215	SS	FS	FS	SF	0.02516
24	FF	FS	FS	SS	0.02143	88	FS	FS	FS	SS	0.00439	152	SF	FS	FS	SS	0.02516	216	SS	FS	FS	SS	0.00515
25	FF	FS	SF	FF	0.51092	89	FS	FS	SF	FF	0.10465	153	SF	FS	SF	FF	0.59977	217	SS	FS	SF	FF	0.12284
26	FF	FS	SF	FS	0.10465	90	FS	FS	SF	FS	0.02143	154	SF	FS	SF	FS	0.12284	218	SS	FS	SF	FS	0.02516
27	FF	FS	SF	SF	0.59977	91	FS	FS	SF	SF	0.12284	155	SF	FS	SF	SF	0.70408	219	SS	FS	SF	SF	0.14421
28	FF	FS	SF	SS	0.12284	92	FS	FS	SF	SS	0.02516	156	SF	FS	SF	SS	0.14421	220	SS	FS	SF	SS	0.02954
29	FF	FS	SS	FF	0.10465	93	FS	FS	SS	FF	0.02143	157	SF	FS	SS	FF	0.12284	221	SS	FS	SS	FF	0.02516
30	FF	FS	SS	FS	0.02143	94	FS	FS	SS	FS	0.00439	158	SF	FS	SS	FS	0.02516	222	SS	FS	SS	FS	0.00515
31	FF	FS	SS	SF	0.12284	95	FS	FS	SS	SF	0.02516	159	SF	FS	SS	SF	0.14421	223	SS	FS	SS	SF	0.02954
32	FF	FS	SS	SS	0.02516	96	FS	FS	SS	SS	0.00515	160	SF	FS	SS	SS	0.02954	224	SS	FS	SS	SS	0.00605
33	FF	SF	FF	FF	2.49448	97	FS	SF	FF	FF	0.51092	161	SF	SF	FF	FF	2.92830	225	SS	SF	FF	FF	0.59977
34	FF	SF	FF	FS	0.51092	98	FS	SF	FF	FS	0.10465	162	SF	SF	FF	FS	0.59977	226	SS	SF	FF	FS	0.12284
35	FF	SF	FF	SF	2.92830	99	FS	SF	FF	SF	0.59977	163	SF	SF	FF	SF	3.43757	227	SS	SF	FF	SF	0.70408
36	FF	SF	FF	SS	0.59977	100	FS	SF	FF	SS	0.12284	164	SF	SF	FF	SS	0.70408	228	SS	SF	FF	SS	0.14421
37	FF	SF	FS	FF	0.51092	101	FS	SF	FS	FF	0.10465	165	SF	SF	FS	FF	0.59977	229	SS	SF	FS	FF	0.12284
38	FF	SF	FS	FS	0.10465	102	FS	SF	FS	FS	0.02143	166	SF	SF	FS	FS	0.12284	230	SS	SF	FS	FS	0.02516
39	FF	SF	FS	SF	0.59977	103	FS	SF	FS	SF	0.12284	167	SF	SF	FS	SF	0.70408	231	SS	SF	FS	SF	0.14421
40	FF	SF	FS	SS	0.12284	104	FS	SF	FS	SS	0.02516	168	SF	SF	FS	SS	0.14421	232	SS	SF	FS	SS	0.02954
41	FF	SF	SF	FF	2.92830	105	FS	SF	SF	FF	0.59977	169	SF	SF	SF	FF	3.43757	233	SS	SF	SF	FF	0.70408
42	FF	SF	SF	FS	0.59977	106	FS	SF	SF	FS	0.12284	170	SF	SF	SF	FS	0.70408	234	SS	SF	SF	FS	0.14421
43	FF	SF	SF	SF	3.43757	107	FS	SF	SF	SF	0.70408	171	SF	SF	SF	SF	4.03541	235	SS	SF	SF	SF	0.82653
44	FF	SF	SF	SS	0.70408	108	FS	SF	SF	SS	0.14421	172	SF	SF	SF	SS	0.82653	236	SS	SF	SF	SS	0.16929
45	FF	SF	SS	FF	0.59977	109	FS	SF	SS	FF	0.12284	173	SF	SF	SS	FF	0.70408	237	SS	SF	SS	FF	0.14421
46	FF	SF	SS	FS	0.12284	110	FS	SF	SS	FS	0.02516	174	SF	SF	SS	FS	0.14421	238	SS	SF	SS	FS	0.02954
47	FF	SF	SS	SF	0.70408	111	FS	SF	SS	SF	0.14421	175	SF	SF	SS	SF	0.82653	239	SS	SF	SS	SF	0.16929
48	FF	SF	SS	SS	0.14421	112	FS	SF	SS	SS	0.02954	176	SF	SF	SS	SS	0.16929	240	SS	SF	SS	SS	0.03467
49	FF	SS	FF	FF	0.51092	113	FS	SS	FF	FF	0.10465	177	SF	SS	FF	FF	0.59977	241	SS	SS	FF	FF	0.12284
50	FF	SS	FF	FS	0.10465	114	FS	SS	FF	FS	0.02143	178	SF	SS	FF	FS	0.12284	242	SS	SS	FF	FS	0.02516
51	FF	SS	FF	SF	0.59977	115	FS	SS	FF	SF	0.12284	179	SF	SS	FF	SF	0.70408	243	SS	SS	FF	SF	0.14421
52	FF	SS	FF	SS	0.12284	116	FS	SS	FF	SS	0.02516	180	SF	SS	FF	SS	0.14421	244	SS	SS	FF	SS	0.02954
53	FF	SS	FS	FF	0.10465	117	FS	SS	FS	FF	0.02143	181	SF	SS	FS	FF	0.12284	245	SS	SS	FS	FF	0.02516
54	FF	SS	FS	FS	0.02143	118	FS	SS	FS	FS	0.00439	182	SF	SS	FS	FS	0.02516	246	SS	SS	FS	FS	0.00515
55	FF	SS	FS	SF	0.12284	119	FS	SS	FS	SF	0.02516	183	SF	SS	FS	SF	0.14421	247	SS	SS	FS	SF	0.02954
56	FF	SS	FS	SS	0.02516	120	FS	SS	FS	SS	0.00515	184	SF	SS	FS	SS	0.02954	248	SS	SS	FS	SS	0.00605
57	FF	SS	SF	FF	0.59977	121	FS	SS	SF	FF	0.12284	185	SF	SS	SF	FF	0.70408	249	SS	SS	SF	FF	0.14421
58	FF	SS	SF	FS	0.12284	122	FS	SS	SF	FS	0.02516	186	SF	SS	SF	FS	0.14421	250	SS	SS	SF	FS	0.02954
59	FF	SS	SF	SF	0.70408	123	FS	SS	SF	SF	0.14421	187	SF	SS	SF	SF	0.82653	251	SS	SS	SF	SF	0.16929
60	FF	SS	SF	SS	0.14421	124	FS	SS	SF	SS	0.02954	188	SF	SS	SF	SS	0.16929	252	SS	SS	SF	SS	0.03467
61	FF	SS	SS	FF	0.12284	125	FS	SS	SS	FF	0.02516	189	SF	SS	SS	FF	0.14421	253	SS	SS	SS	FF	0.02954
62	FF	SS	SS	FS	0.02516	126	FS	SS	SS	FS	0.00515	190	SF	SS	SS	FS	0.02954	254	SS	SS	SS	FS	0.00605
63	FF	SS	SS	SF	0.14421	127	FS	SS	SS	SF	0.02954	191	SF	SS	SS	SF	0.16929	255	SS	SS	SS	SF	0.03467
64	FF	SS	SS	SS	0.02954	128	FS	SS	SS	SS	0.00605	192	SF	SS	SS	SS	0.03467	256	SS	SS	SS	SS	0.00710

Table B.7 Scenario Table

APPENDIX C: DETAILED RESULTS OF THE SENSITIVITY ANALYSIS

C.1 Relaxed Budget

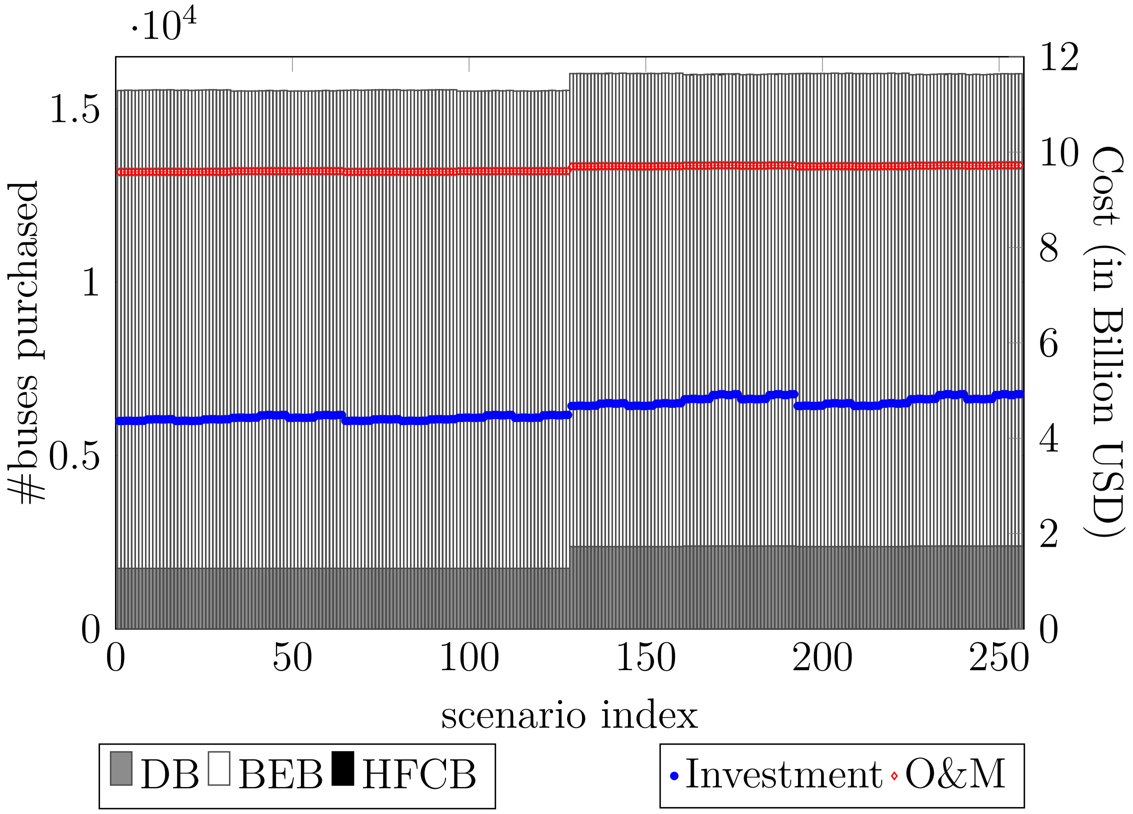

Figure C.1 Relaxed Budget

Figure C.1 represents the case where the annual budget is set at 300 million USD. The optimization process took 5,888 seconds, resulting in an objective function value of 13,586,698,671 USD. After rounding the variables, the objective function value increased to 13,615,884,770 USD.

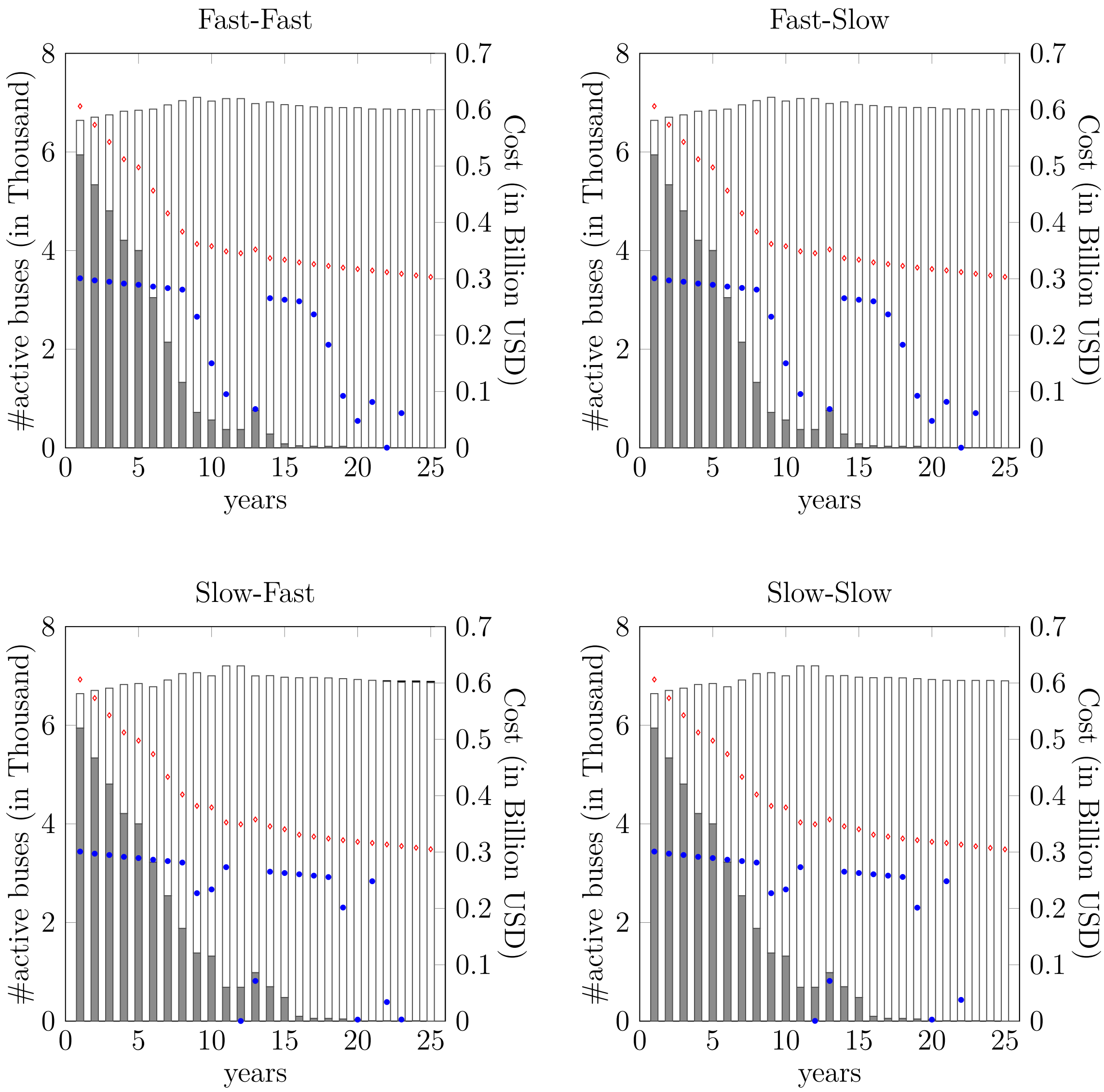

Figure C.2 Relaxed Budget - four specific scenarios.

In scenarios where BEBs improve slowly, a small number of HFCBs are purchased in the final time periods. Since HFCBs are starting to become competitive in terms of purchase and O&M costs, they are being selected for routes where BEBs are inherently difficult to operate, reducing the overall fleet size. This occurs even in the Slow-Slow scenario. In contrast, no HFCBs are purchased in scenarios where BEBs improve rapidly.

C.2 Strict Emission Constraints

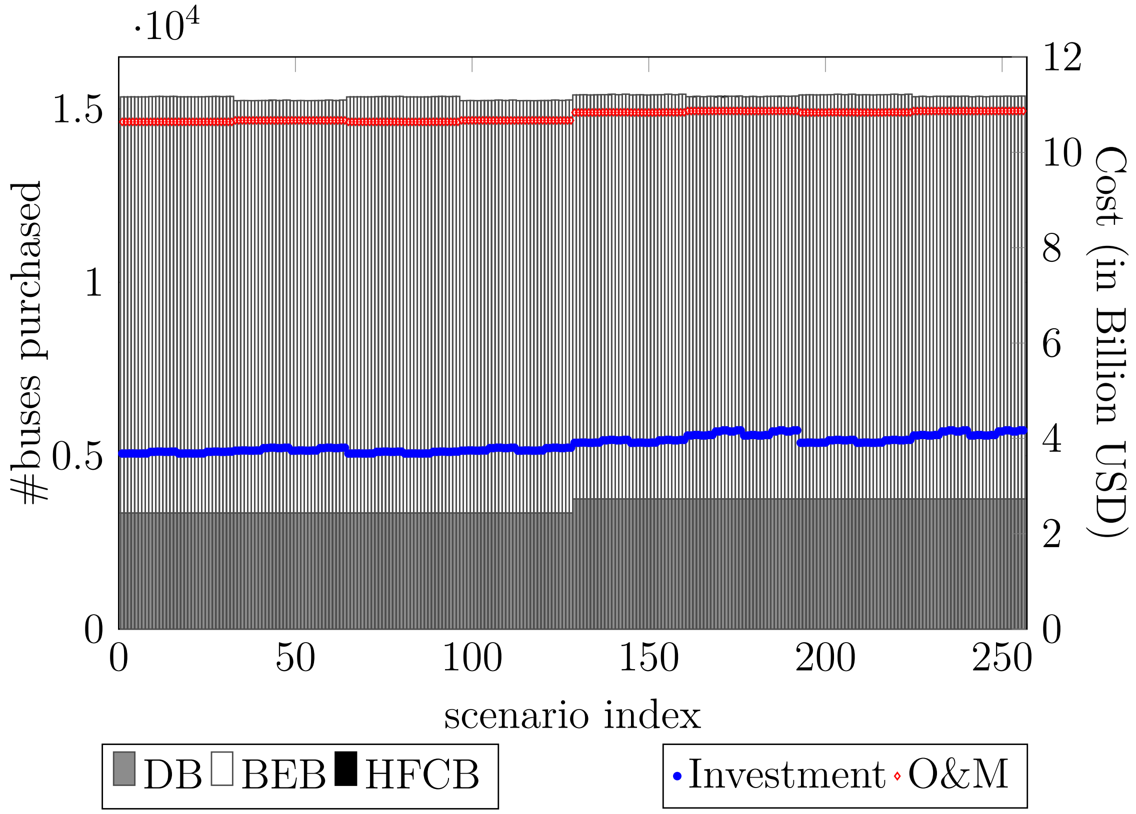

Figure C.3 Strict Emission Constraints

Figure C.3 represents the case with only zero emission limits in the final period, and without any intermediate targets. The optimization process took 4,877 seconds, resulting in an objective function value of 14,133,211,491 USD. After rounding the variables, the objective function value increased to 14,165,320,512 USD.

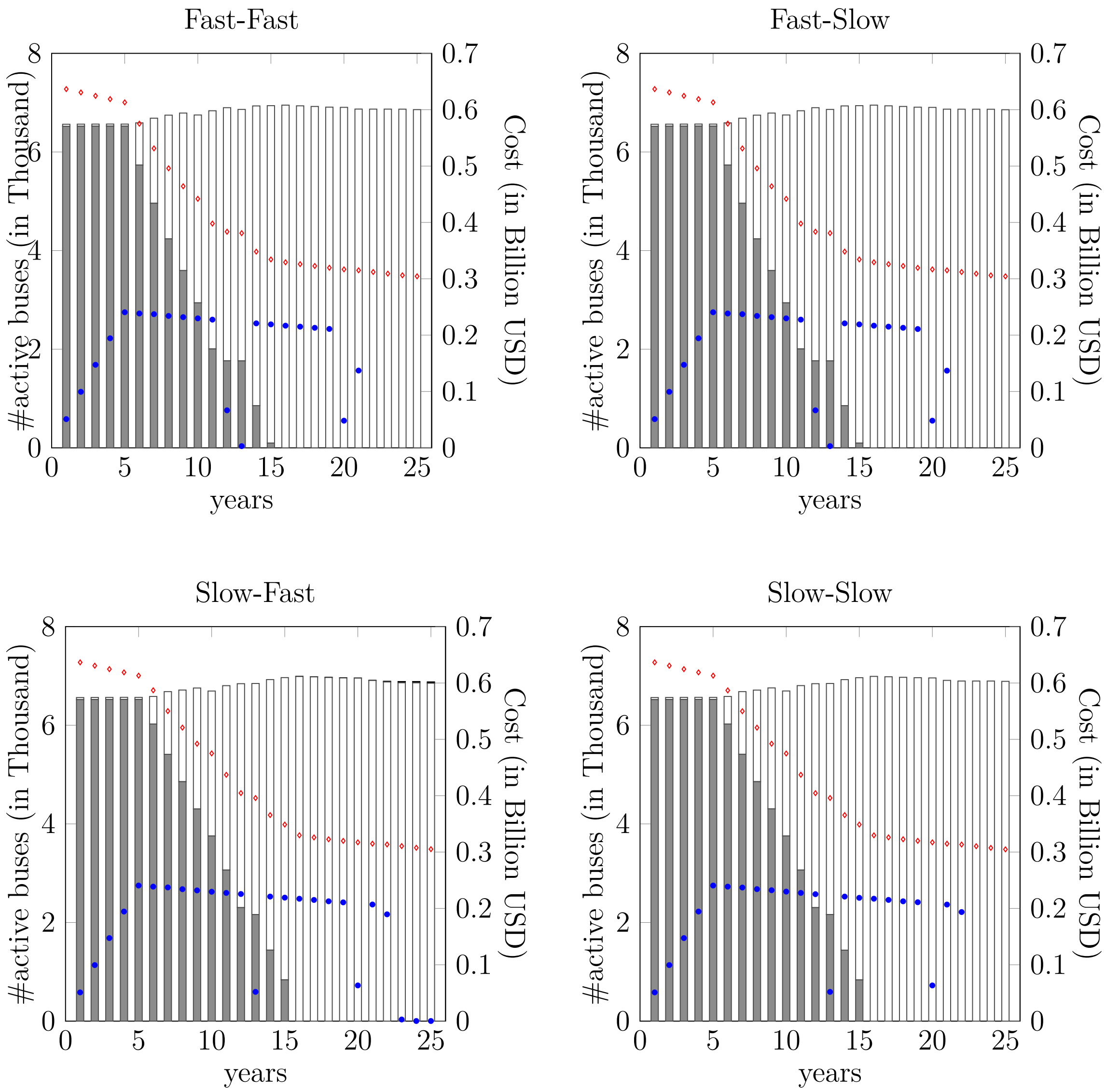

Figure C.4 Strict Emission Constraints - four specific scenarios

C.3 Reduced Hydrogen Price

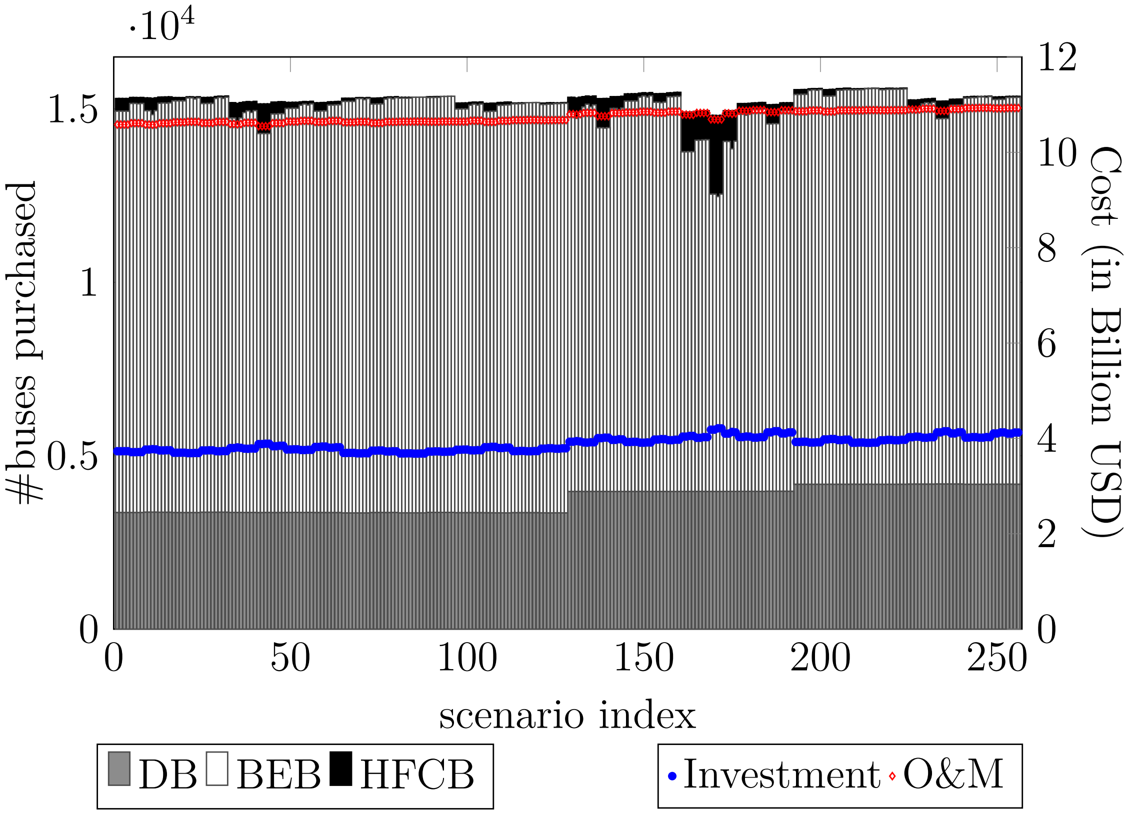

Figure C.5 Reduced Hydrogen Price

Figure C.5 represents the case where hydrogen price is reduced to 2 USD per kg. The optimization process took 6,133 seconds, resulting in an objective function value of 14,099,073,373 USD. After rounding the variables, the objective function value increased to 14,129,697,437 USD.

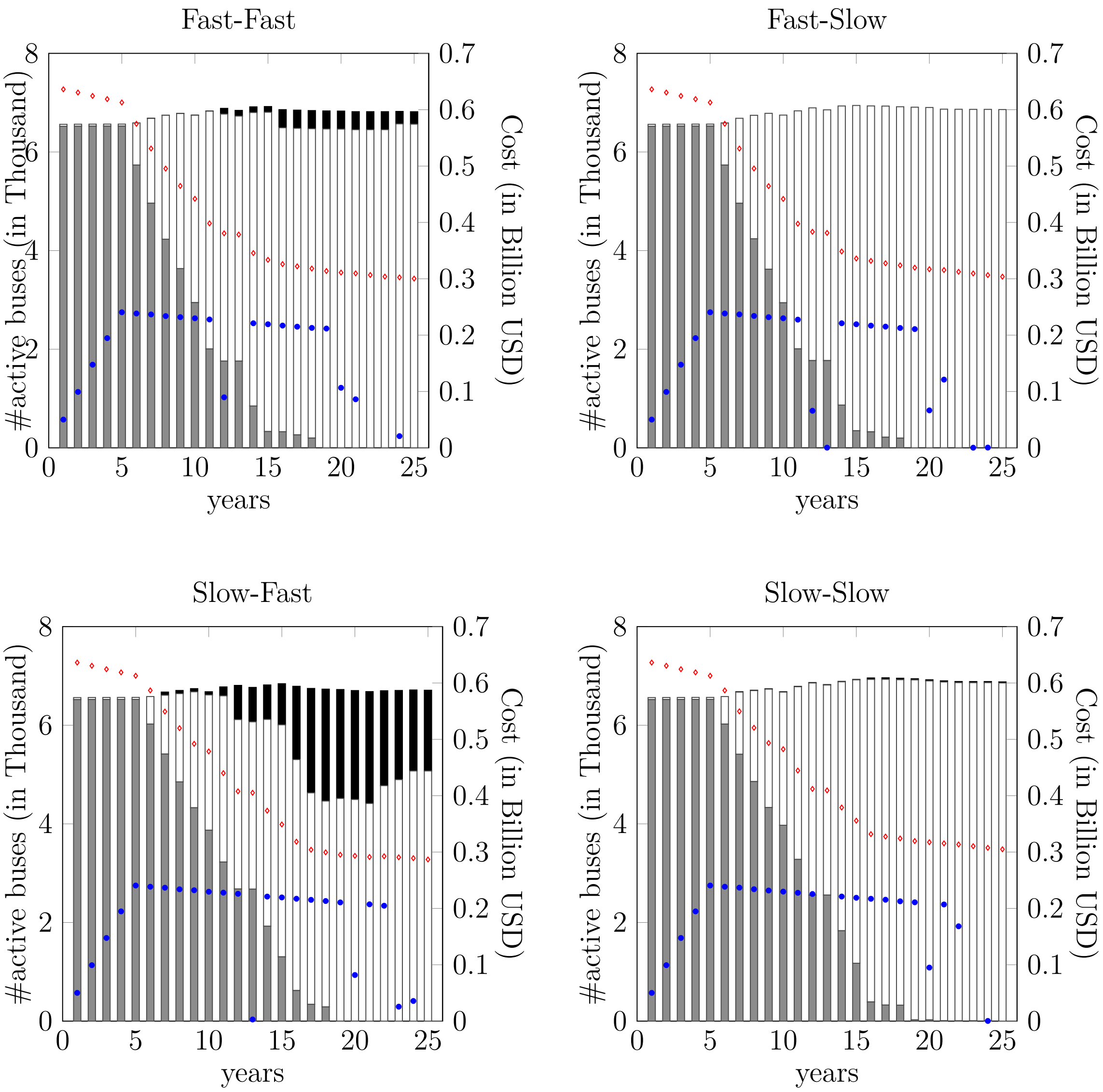

Figure C.6 Reduced Hydrogen Price - four specific scenarios

APPENDIX D: DETAILED RESULTS OF MODEL COMPARISON

D.1 Base Case - Simplified Assignments

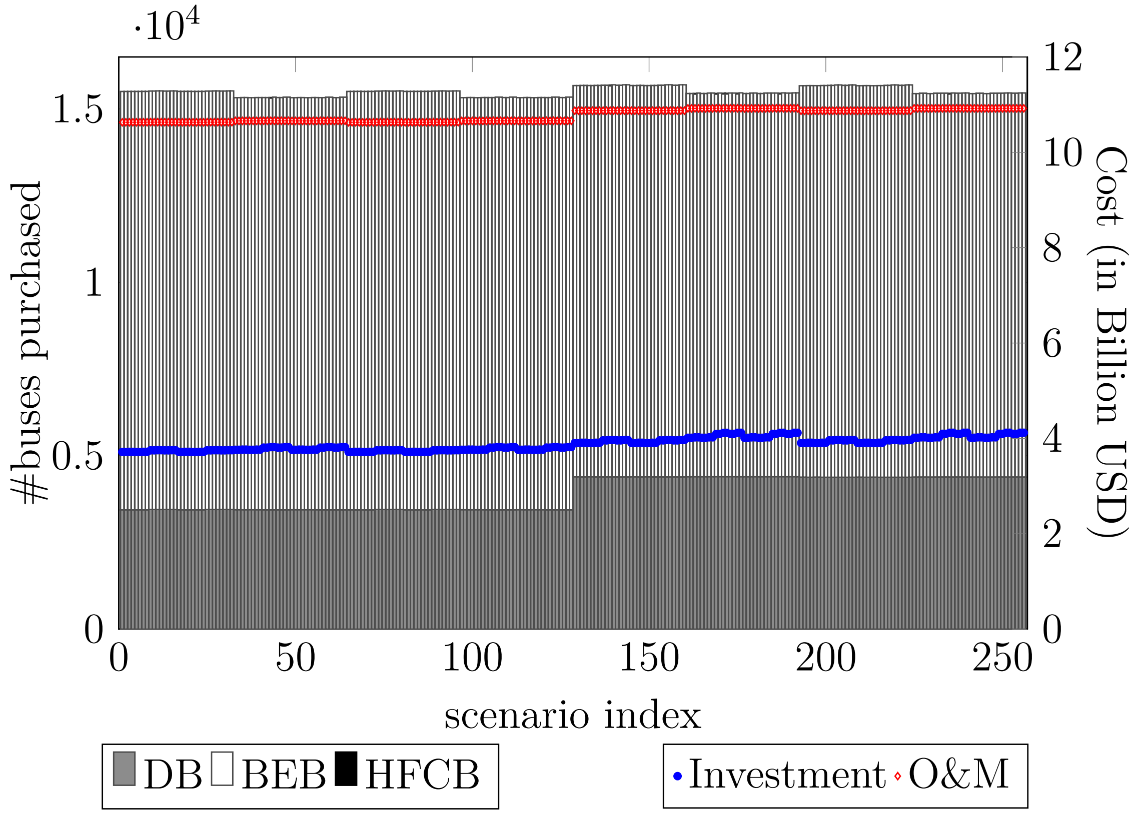

Figure D.1 Base Case with Simplified Assignments

Figure D.1 represents the simplified assignments version of the Base Case. In this case, we assume that for route-bus length pairs with a higher demand in the winter, the buses assigned to a cluster will remain in that cluster on all other seasons. However, we adjust the O&M costs based on the seasonal difference in demand. The optimization process took 1,770 seconds, resulting in an objective function value of 14,111,317,685 USD. After rounding the variables, the objective function value increased to 14,136,930,170 USD.

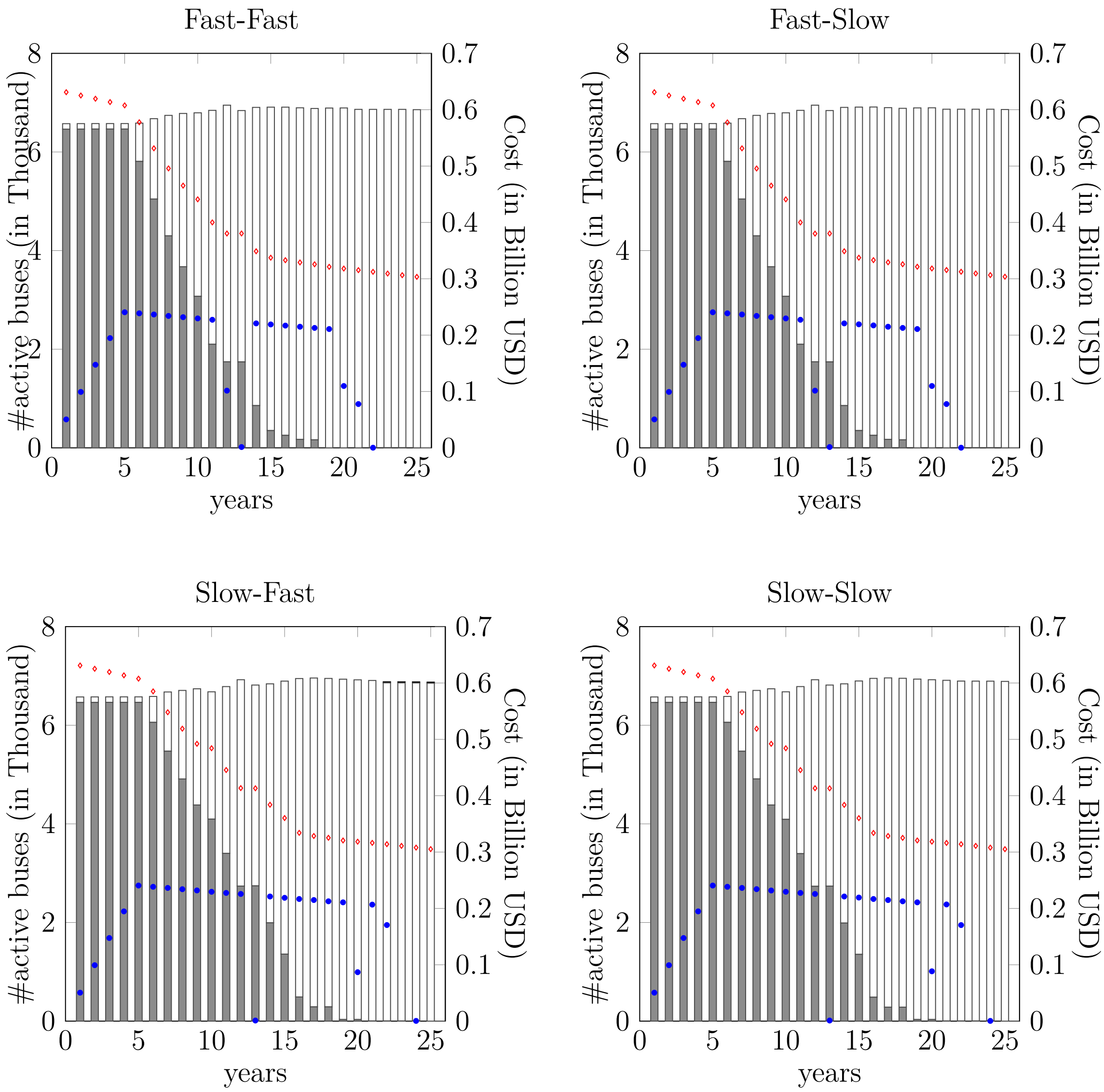

Figure D.2 Base Case (Simplified Assignments) - four specific scenarios

D.2 Extended Scenario Tree - 3 By 2

We present the results of the Extended Scenario Tree - 3 By 2 case in Figure D.3. In this case, three branches for BEB technological improvements and 2 branches for HFCB technological improvements are considered in each stage. Similar to D.1, we simplify the assignment decisions for route-bus length combinations having higher demand in the winter. CPU time is 20,452 seconds, the total expected costs is 14,131,413,878 USD, which increases to 14,158,075,529 USD after rounding the variables.

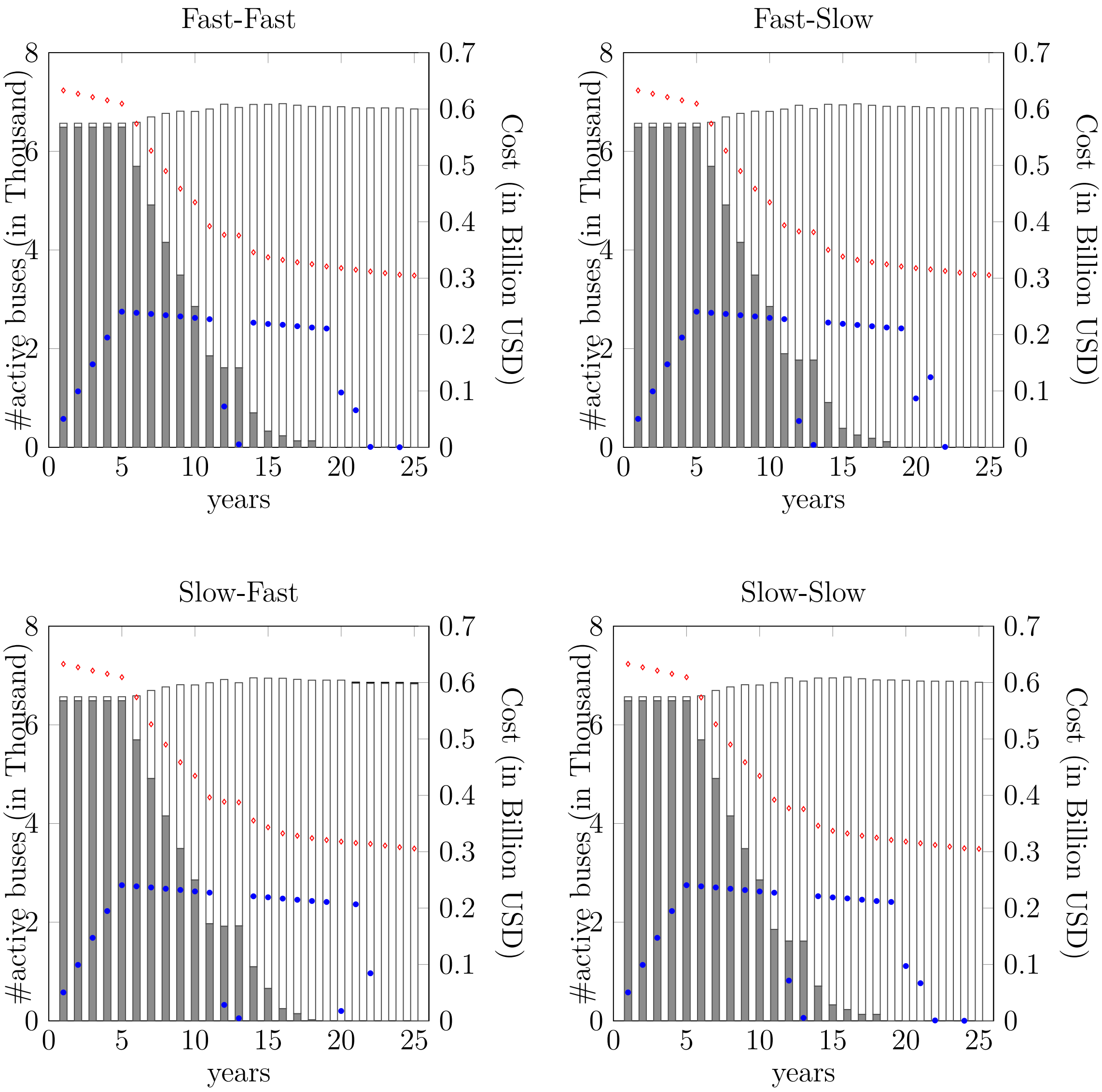

Figure D.3 Extended Scenario Tree (3 By 2) - four specific scenarios

D.3 Extended Scenario Tree - 2 By 3

We present the results of the Extended Scenario Tree - 2 By 3 case in Figure D.4. In this case, two branches for BEB technological improvements and three branches for HFCB technological improvements are considered in each stage. We used simplified assignment decisions, similar to the simplified base case (Section D.1).

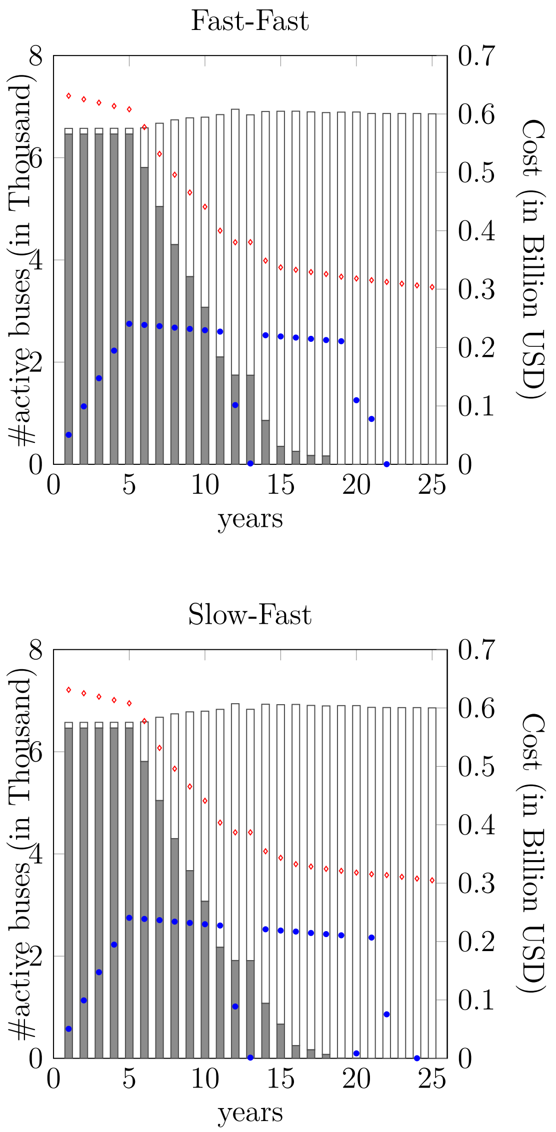

Figure D.4 Extended Scenario Tree (2 By 3) - four specific scenarios

CPU time is 15,210 seconds and the total expected cost is 14,111,299,422 USD, which increases to 14,137,384,326 USD after rounding the variables.

APPENDIX E: DYNAMIC DEMAND

The growth rate of Istanbul's population has been decreasing since 2017, and in 2023, the population was lower than in 2022 (Statista, 2025; TUIK, 2024). This suggests that the population has perhaps stabilized. In addition, the number of bus lines and the number of bus lines bus stops have stabilized around 850 and 15000, respectively, over the last few years (IETT, 2023). Therefore, we do not expect significant changes in demand for buses in Istanbul. On the contrary, the municipality's current focus is on expanding the metro network by opening new lines and stations, rather than growing the bus network. Considering these factors, we chose not to model changes in demand as we do not foresee a meaningful impact of this aspect in our analysis.

Nevertheless, to see the effects of a hypothetical change in demand, we performed a sensitivity analysis in which we increase the demand by 5% every five years by randomly adding trips. Algorithm 1 was run from scratch based on the new schedules, and all the other parameters including DSR, average distance covered, and O&M costs were recalculated accordingly.

The optimization process took 4,853 seconds, resulting in an objective function value of 15,074,254,160 USD. After rounding the variables, the objective function value increased to 15,110,801,090 USD. As expected, the objective function value is 6.7% higher with respect to the Base Case due to the need for a higher number of buses. The results (Figures E.1 and E.2) indicate that even with increasing demand, the transition is quite similar to the Base Case. These results suggest that our conclusions remain valid even under this new case with increased demand.

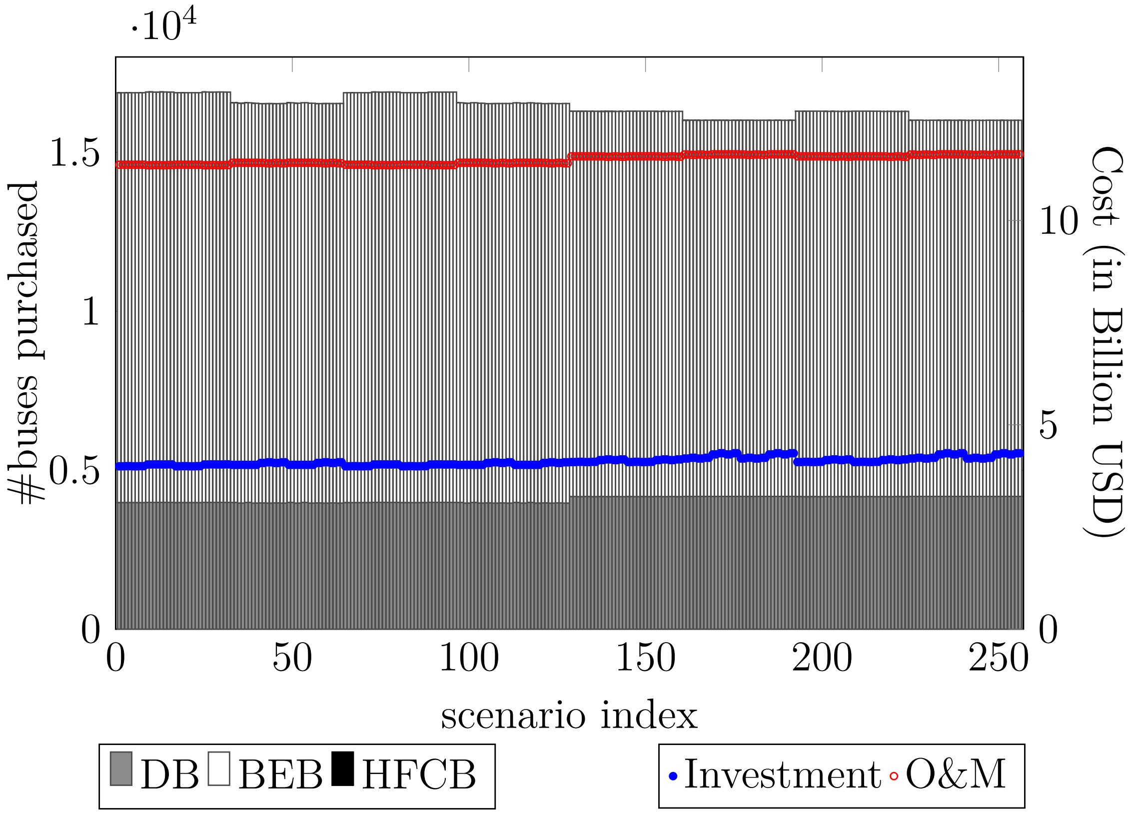

Figure E.1 Dynamic Demand

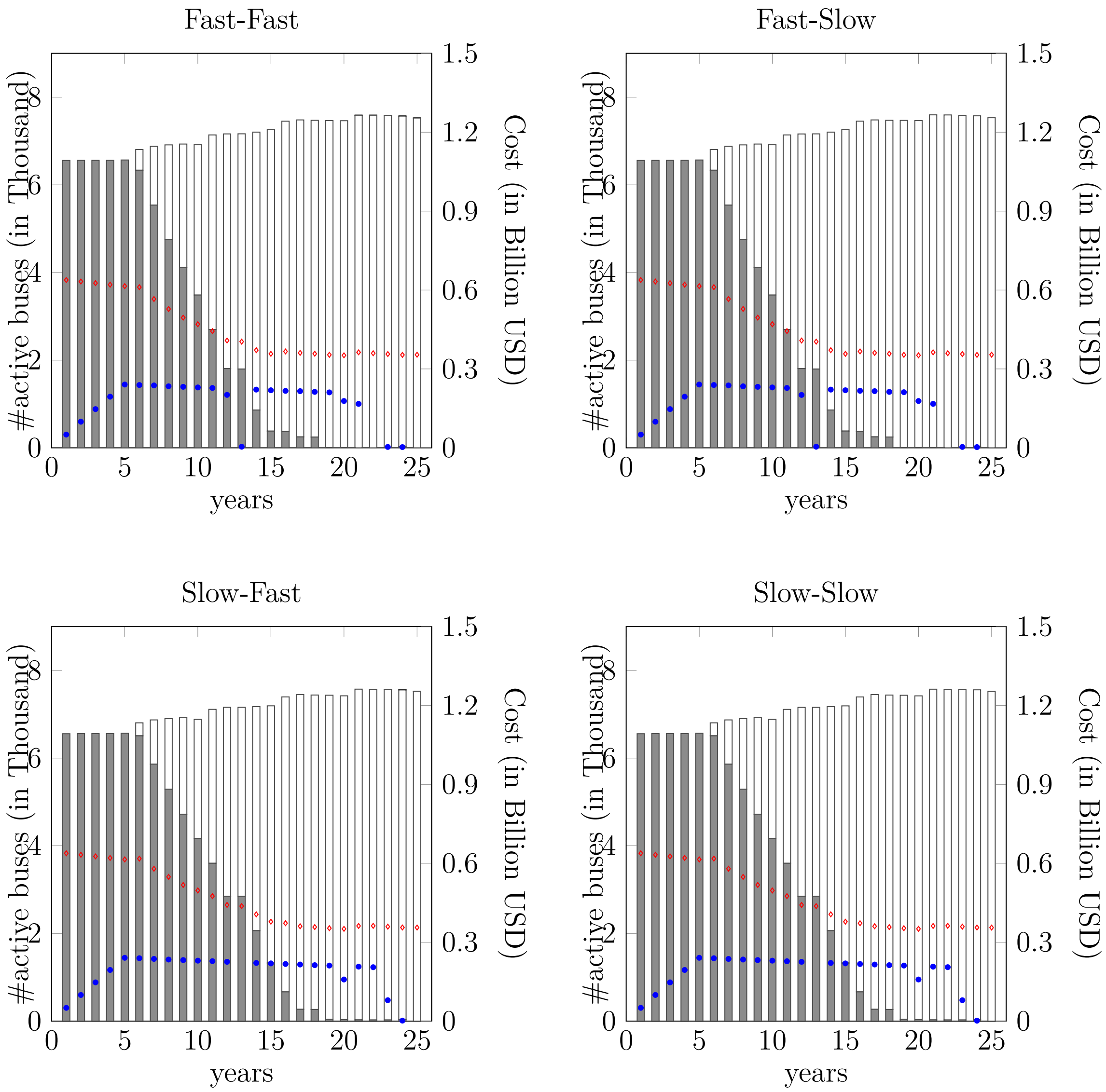

Figure E.2 Dynamic Demand - four specific scenarios