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MasterThesis

Integrating Electric Vehicles with Smart Buildings using Temporal Planning

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Abstract

Commercial buildings often rely on stationary batteries to address emergency power needs and control energy expenses. However, the capital and maintenance costs associated with stationary batteries are prohibitively high. Concurrently, Electric Vehicles (EVs) spend roughly 95% of their operational lifespan in an inactive state, representing a substantial resource under utilization. The increasing prevalence of EVs on the road necessitates a significant expansion of energy resources to accommodate EV charging demands. Vehicle-to-Building (V2B) technology emerges as a solution, harnessing the energy storage capacity of EVs to manage both heavy and light building loads. This not only ensures occupant comfort and safety but also reduces EV charging costs and optimizes energy consumption.

This thesis endeavors to establish a proof of concept for V2B integration, specifically by combining EVs with smart buildings through the application of Temporal Planning, a subdomain of Artificial Intelligence (AI) Planning. The Planning Domain Definition Language (PDDL) is employed to model the domain and problem, utilizing temporal planning versions PDDL 2.1 and PDDL 2.2, which accommodate numeric fluent constraints capable of dynamic changes over time. Timed Initial Fluent (TIF) and Timed Initial Literal (TIL) constructs are employed to modify numeric fluent and predicate values as needed. By incorporating durative actions, representing actions occurring over time, the plan effectively integrates EVs with smart buildings. The resulting plan includes a set of actions to schedule EV charging and discharging, aligning with the building's energy demand and ensuring occupants needs and comfort over a 24-hour period.

The V2B model encompasses various factors, including energy market dynamics and EV-specific information such as EV entering and leaving times, State of Charge (SOC), daily driving distance, minimum charging thresholds, and EV priority levels. It also integrates environmental data relevant to the building, encompassing occupancy patterns, external natural light conditions, current temperature, and operating hours. These elements are harmoniously integrated into a domain model and an associated problem file. The proposed model leverages the capabilities of the Partial Order Planning Forwards – TIF (POPF-TIF) planner, adept at resolving TIFs and TILs, to generate a comprehensive plan for seamlessly integrating EVs with smart buildings and managing building loads efficiently.

In the evaluation, the performance of the POPF planner in handling temporal constraints, such as TIFs and TILs, is assessed to ensure the efficient integration of EVs with smart buildings. The impact of various parameters and values on planner performance is analyzed, providing insights into the optimization of energy utilization, cost reduction, and overall sustainability in commercial buildings.

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List of Acronyms

AI Artificial Intelligence

DSM Demand Side Management

PDDL Planning Domain Definition Language

TIL Timed Initial Literal

TIF Timed Initial Fluent

GBP Green Building Programme

CO2 Carbon dioxide

EU European Union

ENTSO-E European Network of Transmission System Operators for Electricity

TSO Transmission System Operators

POPF Partial Order Planning Forwards

TOU Time-Of-Use

DR Demand Response

IPC International Planning Competition

LPG-TD LPG for Temporal planning with Disjunctive actions

CPT Conformant Planning Toolkit

AC Air Conditioner

Min Minimum

HVAC Heat Ventilation Air Conditioner

REST Representational State Transfer

API Application programming interface

IT Information Technology

HTTP Hypertext Transfer Protocol

SOC State Of Charge

DOD Depth Of Discharge

ECU Electronic Control Unit

EV Electric Vehicle

PV Photovoltaic

PEV Plugin Electric Vehicle

RTP Real Time Prices

CHP Combined Heat and Power

CCHP Combined Cooling, Heat, and Power

BESS Battery Energy Storage Systems

DER Distributed Energy Resources

OEMA Optimal Energy Management Algorithm

1 Introduction

1.1 Motivation

The rising prevalence of electric vehicles (EVs) represents a formidable challenge for conventional power grids, which predominantly rely on fossil fuels [DO], [KD11]. With the forecasted exponential increase in EV adoption, as indicated by the International Energy Agency's projection of 250 million EVs on the road by 2030, there arises a pressing need for a substantial surge in energy resources to accommodate EV charging [CBN+17]. This burgeoning energy demand from EVs can have multifaceted consequences on the power grid, encompassing issues such as power losses and escalated energy costs due to heightened demand [Cle10]. The unregulated proliferation of large-scale EV charging could exacerbate these problems, endangering grid stability, increasing overload risks, and undermining the benefits of green energy supplies [Reh20].

Additionally, the widespread growth of EVs has unveiled a pronounced inefficiency—research has revealed that most EVs remain inactive for approximately 95% of their operational life, representing a significant under utilization of resources [P13]. This untapped potential offers a substantial opportunity, particularly given the positive trajectory of EV battery technology. Over the years, the cost of EV batteries has witnessed a significant decrease, plummeting from $1000/kWh in 2010 to a mere $273/kWh in 2016 [Fin]. This downward trend is expected to continue, providing fertile ground for optimizing energy utilization and enabling seamless grid integration.

EVs, dispersed across various locations, hold the potential to function as a dynamic energy reservoir, effectively becoming a rolling accumulation system. This adaptable system enables the smoothing of energy peaks, the absorption or contribution of energy to the buildings, and the provision of energy as required, thereby mitigating the challenges associated with uneven energy demand [LHD+18].

On the other hand, commercial buildings are notorious for their elevated operational expenses. The release of substantial CO2 levels from the commercial buildings is primarily because of their substantial energy requirements as per the report of European Green Building Programme (GBP) [DAg]. Furthermore, energy consumption in Europe is distributed among diverse end-user sectors, with a noteworthy proportion attributed to commercial and residential buildings, constituting 38.7% of the total energy consumption [Ba]. Particularly, Germany, as one of Europe's largest economies, shoulders a substantial portion of this energy burden due to its expansive commercial and residential infrastructure. In recent times, Germany has undertaken various policies and initiatives to champion energy efficiency within buildings and reduce energy expenditures. These measures encompass the adoption of renewable energy sources like wind and solar power, as well as the utilization of energy-efficient building materials and technologies. Nonetheless, the challenge of high energy costs in the buildings persists as a formidable obstacle to the German economy, necessitating further measures to tackle this predicament [Ba].

Improving energy efficiency within its member states has become a core element of the European Union's (EU) energy policy [Eur14]. Under the initiative known as GBP, established by the European Commission, efforts have been actively underway to advance energy efficiency, with the goal of enhancing efficiency in buildings and lowering energy expenses [GNN+]. The EU has additionally implemented cost-effective minimum energy performance criteria for new construction projects and for the renovation or upgrading of existing buildings, including the replacement or enhancement of building components. These criteria are an integral part of the comprehensive Energy Performance of Buildings Directive [Eur19].

In the domain of commercial buildings, stationary batteries have traditionally been relied upon to supply critical loads during emergencies and manage energy costs. However, the capital investments and ongoing maintenance expenses associated with stationary batteries are notably high [LPT14]. The integration of EVs with smart buildings introduces an innovative solution to these predicaments. Leveraging the batteries of EVs as a distributed storage system offers the potential to furnish backup power during unforeseen emergencies while concurrently alleviating peak energy demand burdens. This synergistic relationship between EVs and smart buildings promises to enhance energy resilience and cost-effectiveness, heralding a paradigm shift in sustainable energy management.

Interest is growing in integrating EVs with smart buildings, enabling commercial buildings to efficiently manage energy consumption and costs. This integration, known as Vehicle-to-Building (V2B) technology, allows for the use of EVs' energy storage to control heavy and light loads in buildings. V2B has the potential to reduce EV costs, lower building energy expenses, and enhance energy efficiency. This integration involves solving the building coordination problem, considering factors like energy costs, EV schedules, and building conditions[GA].

Demand-Side Management (DSM) stands as a formidable solution for tackling the complexities of building coordination problem. DSM encompasses a comprehensive array of strategies geared towards enhancing energy cost-effectiveness and operational efficiency [PD]. By integrating advanced technologies such as sensors and actuators, buildings are endowed with the capability to make informed decisions pertaining to their energy usage. This transformation effectively renders buildings 'smart,' enhancing the overall experience for occupants while simultaneously reducing operational expenses and bolstering energy efficiency. Furthermore, this intelligent infrastructure extends its benefits to energy producers and the EVs can also be integrated, allowing them to strategically shape load demand profiles for enhanced grid management and optimization [PD].

AI planning represents a potent technique with the potential to unlock energy efficiency in buildings and surmount the intricate challenges of integrating EVs into smart building systems. By orchestrating actions automatically and adaptively, AI planning can attain predefined objectives while accommodating individuals' requirements and conserving energy resources [Ga04]. Nevertheless, traditional AI planning falls short when it comes to accommodating the quantitative and time-related aspects of building dynamics, thus constraining its effectiveness. Temporal planning, an extension of AI planning, offers an exceptionally rich expressive capacity and an array of mechanisms tailored for addressing highly constrained problems [GA]. Embracing temporal planning can yield even more efficient and finely tuned strategies for conserving energy, positioning it as an invaluable tool in advancing the European Union's objectives for enhancing energy efficiency.

1.2 Objective of the thesis

In this research, we have leveraged the European Network of Transmission System Operators for Electricity (ENTSO-E), which represents the transmission system operators (TSOs) of 35 European countries and provides energy prices for Germany [Ent]. Our study focuses on DSM in commercial buildings, utilizing temporal planning techniques to integrate EVs with smart building. This involves the controlled management of various types of loads within the building and the strategic scheduling of EV charging and discharging, considering factors such as availability, duration of stay, priority, and state of charge (SOC) based on energy market.

The prioritization of EV charging and discharging is determined by multiple criteria, including arrival time, departure time, SOC, battery capacity, and trip distance. Importantly, our approach places a strong emphasis on the comfort and efficiency of building occupants, and as such, it disregards measures related to building structure. Instead, it concentrates on key variables such as operating hours, occupancy levels, daylight levels, the optimal temperature range and energy prices, constructing a fictional yet realistic DSM domain based on these factors. To address these complex optimization challenges, we employ temporal planning techniques. Specifically, we utilize the Partial Order Planning Forwards (POPF) planner to compute plans that outline the most efficient and effective means of achieving predefined goals while maintaining optimal conditions for building occupants.

Our evaluation involved simulating all the variables for building and EV variables to assess the performance of the POPF planner in terms of search state space and time to compute the plan. Leveraging energy market prices from ENTSO-E and the integration of EVs into smart buildings, our approach aims to boost energy efficiency and cut energy costs. By dynamically adjusting energy consumption based on changing factors such as energy prices, EV schedules, and building characteristics, our research supports the development of energy-efficient commercial buildings and promotes the use of renewable energy, contributing to a sustainable energy future.

1.3 Outline

The thesis comprises seven chapters. Chapter 1 introduces the research's motivation and objectives. Chapter 2 offers background information on EV concepts, V2X technology, peak shifting, charging types, battery degradation, energy market prices, demand-side management (DSM), the building coordination problem, AI planning, PDDL, temporal and numeric planning, and various temporal planning tools and Chapter 3 reviews related state of the art research and out research contribution. Chapter 4 outlines the system's architectural design. Chapter 5 delves into system implementation, covering pre-processing, the planning model, post-processing, and the full day plan output. Chapter 6 focuses on evaluation, including experimental design, result analysis, and summarizing findings. Lastly, Chapter 7 presents conclusions and future work suggestions. A bibliography is provided at the end of the thesis.

2 Background Information

2.1 Demand-Side Management (DSM)

Demand-Side Management, often abbreviated as DSM, represents a suite of strategies directed at optimizing energy consumption from the consumer's perspective. This collection of initiatives encompasses a diverse range of measures, such as the utilization of advanced materials to enhance energy efficiency, the introduction of intelligent energy pricing structures that offer incentives for specific consumption patterns, and the real-time control of distributed energy resources [PD].

This section will provide an extensive overview of the primary categories within DSM and delve into the potential advantages and challenges associated with each. By categorizing DSM, we can develop a deeper comprehension of its multifaceted applications and pinpoint areas where its effectiveness can be maximized. Understanding these benefits and challenges is paramount when implementing DSM, as they have a direct bearing on the success of these initiatives.

DSM incorporates a cluster of energy efficiency measures with the primary goal of curbing overall energy consumption while maintaining service quality. Fueled by motivations like conservation, environmental stewardship, and cost-effectiveness, these measures can effectively trim peak energy demand. Illustrative examples encompass equipment upgrades, such as the replacement of traditional incandescent bulbs with energy-efficient compact fluorescent lamps, as well as the deployment of sensors to identify high-energy-consuming devices. These initiatives, when executed effectively, yield substantial cost savings and a noticeable reduction in energy utilization during peak periods [PD].

Time-Based Energy Pricing

Time-based energy pricing represents another dimension within the realm of DSM, a concept that entails the adjustment of energy tariffs during specific time intervals. This category encompasses a variety of pricing structures, including:

1. Time-of-Use (TOU) Pricing: This scheme involves the alteration of rates during designated time segments, which can span hours, days, or even entire seasons. These rate adjustments are typically incorporated into the contractual agreements between energy providers and consumers, resulting in infrequent rate revisions over time [PD].

2. Day-Ahead Pricing: In the realm of day-ahead pricing, electricity prices are communicated to consumers a day in advance. Suppliers may harness network or load data collected from consumers to refine and optimize their pricing models [DG12].

3. Real-Time Pricing: In contrast, real-time pricing continually updates energy prices applied to consumers on an hourly basis, driven by fluctuations in wholesale prices. These dynamically shifting price structures have the potential to motivate consumers to shift their energy consumption to periods characterized by lower prices, thereby contributing to an overall reduction in energy usage during peak hours.

This array of time-based energy pricing strategies plays a pivotal role in shaping consumer behavior and optimizing energy consumption patterns, ultimately advancing the objectives of DSM within the energy landscape.

Demand Response

Demand Response, abbreviated as DR, entails the modification of customer electricity consumption patterns during peak periods, aimed at enhancing system reliability and optimizing infrastructure [KPH]. It's important to note that incentive-based DR, including direct load control and emergency programs, falls outside the scope of this thesis, as it necessitates the active involvement of utility or grid operators. Additionally, the category of Spinning Reserve doesn't pertain to the scope of this thesis.

2.2 Building coordination problem

In the current landscape of building automation systems, the prevailing approach relies on rudimentary reactive control and feedback mechanisms. While undoubtedly an improvement, these systems have notable limitations. These limitations encompass a lack of awareness regarding occupants' needs, inefficiencies in energy utilization, and a conspicuous absence of synchronized and the EVs cannot be fully integrated with them as expected. The overarching aspiration is to empower the devices and systems within a building to autonomously decide, prioritize, and execute actions that not only optimize occupant satisfaction but also curtail energy consumption by the help of EVs. This formidable challenge is commonly referred to as the "building coordination problem"[GA].

2.3 Peak Shifting

Peak shifting is an energy management strategy that leverages EVs to optimize energy consumption within buildings. During periods of high electricity demand, known as peak hours, electricity prices tend to be higher. EVs can help mitigate these costs by discharging stored energy from their batteries into the building when demand is at its peak [PDK12]. This effectively reduces the building's reliance on expensive grid power during these peak periods, resulting in significant cost savings [MK15]. Peak shifting not only benefits building owners by lowering energy expenses but also contributes to grid stability by reducing strain during peak demand times. It is a valuable strategy for enhancing both cost-efficiency and overall energy sustainability [PDK12].

2.4 Types of Charging

EV charging methods can be categorized into different types based on how energy is supplied to the vehicle.

Unidirectional Charging

Unidirectional charging refers to the standard method of charging an electric vehicle (EV) from a power source. In this approach, the EV battery is charged from an external power supply, typically during off-peak hours [NB].

Bidirectional Charging

Bidirectional charging, often referred to as V2B (Vehicle-to-Building), allows the EV battery to discharge energy back into the building or even sell surplus energy to the gird. V2B systems are commonly integrated into building microgrids, working alongside stationary battery energy storage systems (BESSs), flexible building loads, and various distributed energy resources (DERs) like photovoltaic (PV) panels, wind turbines, combined heat and power (CHP) systems, and combined cooling heat and power (CCHP) systems [NB].

2.5 Vehicle-to-X (V2X) Technologies

The realm of Vehicle-to-X (V2X) technologies introduces a groundbreaking paradigm where the energy stored in EVs plays a pivotal role in actively managing energy consumption and cost dynamics across diverse applications denoted as X. These applications encompass vehicle-to-home (V2H), vehicle-to-building (V2B), and vehicle-to-grid (V2G) interactions. The incorporation of V2X technologies holds immense potential, offering advantages to EV owners, grid operators, and building proprietors. It serves as a strategic solution to mitigate the high cost of EVs, curtail building energy expenditures, and provide dependable emergency backup services [GZ16].

V2G: Vehicle-to-Grid

Vehicle-to-grid (V2G) technologies enable EVs to not only consume energy but also serve as potential energy sources for the grid. This bidirectional interaction empowers distribution system operators to access EV energy for ancillary services while compensating vehicle owners for their participation. V2G systems adapt to renewable energy source fluctuations, with EVs supplying excess energy to the grid during peak electricity prices and recharging when prices are low. Additionally, V2G helps maintain grid frequency stability by regulating energy discharge or charge from EVs to the grid.

V2B: Vehicle-to-Building

Vehicle-to-building (V2B) technology introduces a pragmatic and resource-efficient approach by harnessing EVs as valuable energy assets for buildings. The fundamental premise of V2B revolves around the seamless exchange of energy between EVs and commercial or residential buildings while steadfastly adhering to the imperative of maintaining optimal environmental conditions within the building. Diverging from the complexities of V2G, V2B thrives on simplicity, eliminating the need for extensive grid infrastructure enhancements or intricate communication systems. Users can seamlessly activate V2B functionality by merely plugging in their PEVs, thereby enhancing energy efficiency with minimal energy losses [LCWG13], [GZ16]. A notable advantage of V2B lies in its potential to curtail battery capital costs by effectively leveraging existing battery resources. By treating electric vehicles as conventional energy consumers, V2B offers a substantial degree of adaptability, thereby enhancing multiple facets of smart building performance [ZC19].

V2H: Vehicle-to-Home

Vehicle-to-home (V2H) is a subset of V2B, where one or more plug-in electric vehicles (PEVs) facilitate energy management within residential buildings. The widespread adoption of V2H and V2B optimizes electricity generation capacity utilization, enhances grid stability and reliability, and diminishes peak-load stress. This is achieved by reducing peak electricity demand, supporting distributed energy generation, and enabling buildings to consume self-generated energy, ultimately bolstering the resilience and efficiency of the power grid [CPRB17].

2.6 Peak Shaving and Demand Charge

Demand charges for commercial buildings are tied to peak power consumption, making them a significant expense. V2B technology can help reduce demand charges by discharging EV batteries when the building experiences high power consumption, thus mitigating peak loads from the grid. This process, known as peak shaving, is a key consideration for both residential and commercial buildings [HMJB09], [NS12], [KHT18], [al15], and [ITRG18].

2.7 Delayed Charging

Delayed charging, often referred to as "just-in-time"charging, is an approach designed to extend the lifespan of EV batteries [NB]. Instead of immediately charging the battery upon arrival, this method involves storing the battery at a lower SOC overnight and subsequently recharging it early in the morning before use. By addressing concerns related to long charging times and limited driving range, delayed charging offers a practical and sustainable solution [NB].

2.8 EV Smart Charging Strategies

Smart charging strategies for EVs involve approaches to optimize the charging process, taking into account factors such as energy cost, grid demand, and building requirements.

Passive Charging

Passive smart charging involves charging the EV during off-peak price hours, such as overnight, without considering the building's energy demand [NB].

Active Charging

Active charging treats the EV as a flexible load and employs systematic control over both charging power and timing to meet various operational objectives. This approach monitors electricity prices and the building's energy demand, adjusting the PEV charging power accordingly. Active charging can effectively reduce both energy and demand charges [NB].

2.9 EV Battery Degradation

Battery degradation is a significant concern in the context of V2B applications, primarily because capacity loss resulting from degradation can reduce the driving range of EVs and potentially increase driver anxiety regarding charging. The phenomenon of battery degradation is multifaceted and influenced by various factors, including temperature, SOC, Depth of Discharge (DOD), C-rate, voltage exposure, and current profile, among others [Smi12].

SOC represents the remaining energy in the battery, while DOD indicates the percentage of energy withdrawn from the battery during use. The C-rate signifies the rate at which the battery is charged or discharged [Mal21]. Engaging in V2B energy arbitrage, which involves discharging the battery when it has a lower SOC, contributes to mitigating battery degradation [Mal21].

Battery Capacity Fade

Battery capacity fade is a significant concern for V2B applications, particularly when compared to stationary batteries, as it directly impacts the driving range and mobility of EVs. While additional discharge cycles can lead to reduced effective battery life, V2B offers benefits when considering battery longevity [NB].

Battery Life Metrics

Battery life is typically characterized by two interconnected measures: calendar life and cycling life.

Calendar Aging: Lithium-ion batteries experience aging even during storage and without active use. Observable effects of calendar aging include a reduction in capacity and an increase in resistance, leading to energy and power loss, respectively. Calendar life specifies the number of years a battery is expected to last and is predominantly influenced by temperature and SOC [Tho18].

Cycling Aging: Cycling life refers to the number of charge-discharge cycles a battery is projected to undergo before reaching a threshold for capacity loss or resistance increase. Cycling aging is additionally dependent on factors like C-rate and DOD [Tho18]. Batteries exhibiting higher calendar aging and lower cycling aging are better suited for V2X applications [NB].

2.10 Artificial Intelligence (AI) Planning

In the realm of AI, there are various problem-solving tools at our disposal, such as making decisions, creating schedules, optimizing processes, and making predictions [Sha21]. AI uses a mix of methods to tackle real-world challenges, including AI planning, machine learning, deep learning, and search algorithms, among others. However, the choice of which method to use depends on the specific problem you're dealing with [Sha21]. The effectiveness of a problem-solving method really hinges on the kind of problem it's dealing with. For instance, some problems can be neatly and efficiently solved with AI planning, while others might prove difficult due to their complexity [Sha21]. Machine learning and deep learning shine when you're dealing with large amounts of data and intricate patterns. But when you need logical reasoning or rule-based decision-making, these methods might not be the best fit. So, picking the right method for the job is crucial to get the best results [Sha21].

AI planning, in particular, is super handy when you're dealing with problems that have lots of possible scenarios, thanks to its clever searching algorithms and smart strategies. It's a method that uses smart techniques to figure out how to get from a starting point to a desired goal [GA16].

Here's how it works: Imagine you have a problem with a beginning state, an end goal, and a bunch of actions you can take to get there. Each action comes with conditions it needs to meet before it can be done (these are called preconditions), and they also have effects, which are like predictions of what will happen if you do the action [GA16]. A plan is essentially a series of actions that, when you follow them starting from the beginning, lead you to your goal. We call this plan a solution to the problem [GA16]. In this world of AI planning, things are pretty straightforward. We assume we can see everything in the environment, it's not changing on its own, and any changes only happen when we decide to take an action. We don't really care how long an action takes; what matters is the order in which we do things. We use a language called PDDL to describe our problems, and this handy tool lets us skip talking about all the small changes in between steps [Sha21].

Now, when we kick it up a notch and look at temporal planning, we're not only concerned about the order of actions but also how long they take but also when these actions happen during the day. This consideration of timing is a crucial aspect of temporal planning, as it helps ensure that actions are scheduled at the right moments to achieve specific goals efficiently [Sha21]. AI planning, especially the classical kind, is pretty great at handling big, complicated problems. It does this by being really clever with how it searches through all the possible solutions. So, whether you're dealing with a simple problem or something more complex, AI planning has got you covered with its smart strategies and algorithms [Sha21].

2.11 Planning Domain Description Language (PDDL)

For the International Planning Competition in 1998, Drew McDermott and colleagues created PDDL (Planning Domain Description Language) [McD00]. Since that time, PDDL has developed into a widely regarded norm for creating and exchanging planning models [FL03]. The purpose of PDDL, which is essentially an AI planning language, is to specify the required inputs for planning issues. It enables us to specify the environment's starting and ending conditions as well as the sequence of steps necessary to move from the starting state to the desired state.

2.11.1 PDDL iterations

The goal of each iteration of PDDL's evolution over time has been to increase the expressiveness and situational adaptability of the language. Here, we provide a brief description of a few of the popular PDDL [GKW+98] versions.

PDDL 1.2

PDDL version 1.2 was first released in 1998. States, goals, and actions, among other fundamental constructs for modeling planning issues, were made available. Despite having some expressive power limitations, it became well-liked in the planning community because of its simplicity [GKW+98].

PDDL 2.1

Version 2.1 significantly expanded PDDL's capabilities by introducing the ideas of time and numerical fluents. This addition created new time points for the start, end, and duration of actions and allowed the modeling of time through actions that have set durations [FL11]. The representation of numerical resources, such as battery charge or materials, was made possible by numerical fluencies. Additionally, PDDL 2.1 made it easier to condition and effect numeric fluents, which allowed for the modeling of resource consumption and requirements [FL11]. Planning can be difficult when dealing with time and numbers, but PDDL 2.1 made AI planning and related approaches more feasible.

PDDL 2.2

The derived predicates and timed initial literals introduced in PDDL 2.2 by Edelkamp and Hoffman in 2004 expand upon the previous version (2.1). Predicate formulas don't need to be repeated in actions thanks to derived predicates, which make it possible to build reusable predicates based on other predicates. This makes it easier to express the connections between predicates [EH04]. Temporal planning is given a useful extension by TILs. They enable us to indicate that a fact becomes true later on in the plan, rather than just at the start [EH04]. When planning, TILs are especially helpful for accurately capturing the environment's initial state and taking time-dependent conditions and constraints into account. Planners can express precisely when certain facts turn true or false by using TILs, which is essential for simulating real-world scenarios where events take place over time [EH04].

TIFs are used in PDDL to represent the fact that a particular condition is true at a particular moment in time in a planning problem. This function is especially helpful in temporal planning, where the timing and sequence of actions are essential to the plan's success [EH04]. TIFs make it possible to represent the environment's initial state more precisely and give planners the ability to take time-dependent conditions and constraints into account when looking for a solution. When modeling real-world scenarios where events take place over time, planners can express that certain facts become true or false at particular points in time by specifying TIFs.

Other PDDL iterations

The idea of soft constraints with assigned costs was introduced in PDDL 3.0, allowing the expression of the significance of user preferences [GL05]. In order to represent uncontrollable changes in the modeled world, PDDL+ added processes and events. Events happen instantly, while processes take place continuously. Events only occur once when their preconditions are satisfied, whereas processes are triggered by preconditions and have an impact on the domain [GRC+].

2.11.2 PDDL Design

The domain description and the problem description, which are typically kept in separate files, are divided into two parts by the way that PDDL is structured to represent a planning problem. By pairing the same domain with various problem files, this division enables the use of the same domain to solve numerous problems.

Domain Description

The PDDL domain description starts with the domain name and lists the particular specifications for that domain. The level and types of issues that a language can address are determined by these requirements, which affect the planner to use [AHK+98]. Predicates are defined next, and then action descriptions with their associated parameters, preconditions, and outcomes follow. In this context, actions are referred to as operators, and actual objects within a planning problem are referred to as parameters. For comprehensive information on the arguments that are acceptable and the EBNF of a domain description, one can refer to the documentation [AHK+98]. Different planners support different language features.

Problem Description

The creation of a problem description in PDDL requires the specification of the objects, initial state, and goal state [AHK+98]. In a problem, objects can take actions, and the problem's initial state is a collection of true predicates. Predicates that aren't explicitly marked as true are taken to be false in the PDDL because it operates under the closed-world assumption [AG]. A collection of true predicates is another definition of the goal state. If the goal description doesn't contain an action expansion [AHK+98], the problem can be solved by a series of steps that, when taken from the initial state, cause the predicates to be true at the conclusion.

2.12 Temporal planning

Traditional planning approaches can help with complex problems in building design and management, but they fall short in some important ways. For instance, because they frequently assume that environments are static, they are inadequate to handle the changing conditions present in modern structures. In addition, traditional AI planning methods frequently are unable to handle time-sensitive constraints and conditions, which are essential for coordinating systems and devices within architectural structures. These planning techniques frequently ignore the idea of concurrent activities, which is a major flaw when attempting to maximize energy efficiency and financial viability [Rin]. International planning competitions have significantly pushed the limits of research since 1998 [Baj]. Realizing the importance of accommodating time and numerical constraints for practical applications, the 2002 international planning conference set forth the challenge to incorporate these elements. This initiative led to the introduction of PDDL 2.1, an upgraded version of PDDL capable of expressing both time-dependent and numerical characteristics of planning realms. Features added in PDDL 2.1, and its subsequent extension PDDL 2.2, include numeric fluent, action durations, durative actions, continuous effects, and derived predicates among others [Baj]. Temporal planning emerged to fill these gaps, offering a robust framework capable of simulating dynamic and time-sensitive scenarios. This methodology allows for adaptable planning that accommodates shifts in situational contexts in real-time [Baj]. Special constructs like TIF and TIL contribute to depicting time-sensitive and contingent states, while the concept of durative actions facilitates the modeling of activities extending over a time span [Baj].

The flexibility of temporal planning allows it to handle complex issues like concurrency, time-sensitive preconditions, action effects over time intervals, numeric attributes, and action durations. Predicates (Boolean conditions) and numerical functions (real-valued variables), also known as numeric fluent, are used in this model to define the environment. These predicates and numerical functions define actions, both continuous and instantaneous [Baj]. The duration of an action, the conditions that must be met, and the results are divided into three categories. While effects materialize post-action and can occur at either the start or end of an action, these conditions are logical statements built using predicates and numerical fluent. Preconditions may be chronologically arranged in one of three ways: before the action begins, before it ends, or at any time during the course of the action [Baj].

The initial conditions of a planning problem in relation to time-based properties are also outlined by time-based planning using TILs and TIFs. TIFs are functional time-to-value mappings for a given initial condition, whereas TILs are propositions that are true at specific times within the initial state [Baj]. Both TILs and TIFs can represent initial states that are liable to change over time, such as the current state of ongoing processes or the availability of resources. By including them, time-based planning models gain complexity, which helps in the solution of more complex problems that call for handling time-varying constraints [Baj].

2.13 Planner

Together with PDDL, which defines the problem to be solved, AI Planners form the basis of the AI Planning process. These planners analyze and decipher the PDDL specifications to produce a solution. The development of the languages used by AI planners has been inextricably linked to its maturation. For instance, while older planners may have difficulty with more complex language versions like PDDL3.0 or PDDL+, some modern planners can. It's important to note that some antiquated syntax constructions have lost favor and are no longer supported by more modern planning tools [pla]. The wide variety of available planners offers varying degrees of language version compatibility, and some are clearly more effective than others at solving particular types of problems or in general. Regarding compatibility with operating systems, the majority of AI Planners are created for Linux-based systems, as noted in citation [pla]. However, some planners have been successfully ported to Windows and Mac, and those created in programming languages like Java are especially suited for this. It's also crucial to emphasize that planners are typically not available in binary format and must be assembled before use [pla].

2.14 Planners for Temporal Planning

In order to create an executable plan, temporal planners use underlying search algorithms to parse both the domain model and the problem instances. The sophistication of these algorithms, as well as the descriptive strength of the domain and problem definitions, all play a role in how effectively the search process works.

Every two years, the International Planning Competition (IPC), which serves as a platform for showcasing innovative automated planning solutions across various domains, is held. A new special track focusing on temporal planning issues was added to the IPC in 2004. The Conformant Planning Toolkit (CPT), LPG-TD designed for temporal planning with disjunctive actions, and POPF, which are among the most effective planners in the market, all have their roots in this competition. These tools are capable of handling both problems with TILs and TIFs [EH05].

One must take into account the particular benefits and drawbacks that each planner offers when choosing one for a given set of temporal problems. While LPG-TD, for instance, excels in terms of speed and scalability, it may not always deliver the best results [EH05]. Contrarily, CPT provides flexibility in handling both conformant and non-conformant planning scenarios, albeit perhaps more slowly [EH05]. Another widely used planner is POPF, which excels at handling both concurrent and sequential action plans. It specializes in creating strategies that take into account the causal interdependencies and temporal dimensions of actions, with an emphasis on issues involving durable actions. It might, however, struggle with complex temporal constraints [EH05].

UPMurphi, which was unveiled at the 19th International Conference on Automated Planning and Scheduling (ICAPS 2009), is another noteworthy addition to the field of temporal planning [PKN16]. Despite using a syntax that slightly deviates from industry standards, UPMurphi can manage TILs and TIFs with ease [PKN16].

2.15 Energy Market Prices

Electricity prices are set one day before they are delivered under the day-ahead pricing mechanism, which is used in electricity markets. The price is determined by the anticipated supply and demand scenarios for the following day. This means that the electricity market operator will set the market-clearing price based on the total supply and demand after electricity suppliers submit their bids for the quantity and price of electricity they can provide. With the aid of this mechanism, the electricity market is able to adjust to shifts in supply and demand while also assisting in making sure that there is an adequate supply of electricity for a fair price [Cra17]. Day-ahead pricing is widely used in electricity markets around the world and is considered a key mechanism for ensuring the efficient and reliable operation of the electricity system [Cra17].

3 Related Work and Research Contribution

3.1 Related Work

The research paper titled "V2B/V2G on Energy Cost and Battery Degradation under Different Driving Scenarios, Peak Shaving, and Frequency Regulations"by Alain Tchagang and Yeong Yoo [TY] explores the use of EV energy for managing energy costs in commercial buildings. It focuses on the concepts of V2B and V2G technologies, aiming to reduce EV and building expenses while providing emergency backup. The research employs multi-objective optimization to address peak shaving and frequency regulation, considering factors like battery state, EV driving scenarios, and operational constraints, resulting in potential electricity bill savings and improved economic benefits for EV batteries with controlled state of charge limits. This paper provides methods and rules for different driving scenarios and a peak shaving algorithm. While our thesis draws on these concepts, we use AI planning techniques and DSM to optimize energy management in smart buildings. Unlike the paper's MATLAB simulation-based approach, our project offers a more advanced and adaptable solution.

In the paper Öptimal Energy Management of V2B with RES and ESS for Peak Load Minimization"[112K], Nandinkhuu Odkhuu, Ki-Beom Lee, Mohamed A. Ahmed, and Young-Chon Kim, presents an optimal energy management algorithm (OEMA) to minimize peak loads during EV charging in a university campus setting. The OEMA algorithm coordinates EV charging and discharging activities based on real-time pricing (RTP), reducing peak power consumption. Our project leverages this strategy, implementing an optimal charging algorithm that considers factors like time, daily usage, and SOC. This approach ensures efficient EV charging, load management, and cost-effective energy consumption in smart buildings, contributing to peak load reduction and enhanced energy efficiency.

The use of AI planning in DSM is discussed in the thesis, ÄI Planning for improved Ventilation Management in Buildings"[Sta21], as a means of reducing the high energy consumption and expense of running office buildings. The temperature and CO2 levels of an office room were adjusted using PDDL language to a safe and comfortable level. During the coronavirus disease (COVID-19) pandemic, the system, which is running with the Optimizing Preferences and Time-Dependent Costs (OPTIC) planner, seeks to ensure a healthy indoor environment while also delivering regular air exchange, increased energy efficiency, lower operating costs, and reduced emissions. It should be noted that this thesis did not utilize some temporal planning elements, such as TILs and TIFs, which may have offered more expressive flexibility to improve energy and cost in building management.

The researchers tackled a new class of metric temporal planning problems that involve both plan trajectory constraints and uncontrollable numerical events in their study, Än Extension of Metric

Temporal Planning with Application to AC Voltage Control"[Pia]. They presented fresh planning techniques and illustrated their strategy with voltage control in Alternating Current (AC) electrical networks, a real-world application domain. They made use of TILs and TIFs as well as the entire functionality of temporal planning. They created the POPF-TIF planner by extending the POPF2 planner to support better search in the presence of numerical events expressed as TIF. To handle the global propagation of nonlinear effects, they also connected their planner to an external solver that computes AC power flows. Through experiments, the researchers demonstrated that their method scales well with network size and the number of controllable network components. The PDDL 2.2 language is extensively used in the paper for temporal planning. However, the research did not place a high priority on cost optimization, which prevented demand-side management from being implemented.

3.2 Research Contribution

Our research contribution is multifaceted, marking a significant departure from prior studies in the field. We have pioneered the integration of EVs with smart buildings through the novel application of Temporal AI Planning, incorporating TILs and TIFs. While earlier work predominantly focused on the financial and economic feasibility of this integration, our project stands out by implementing the V2B concept via Temporal AI Planning. This innovative approach has not been explored before, setting our research apart. While some previous papers conducted basic simulations to demonstrate the concept, we take a step further by treating EVs as integral components of the building's DSM. We harness real-time energy prices, EV schedules, and smart building loads to ensure optimal energy usage and cost savings, marking a transformative shift in energy management.

Furthermore, our approach exhibits remarkable versatility and adaptability, rendering it compatible with nearly any smart building and EV configuration. Our top priority is the seamless integration of EVs with smart buildings without compromising the occupants' comfort or energy requirements. Through the implementation of Temporal AI Planning, TILs, and TIFs, we have crafted a methodology that accommodates the unique demands of each building and EV fleet, making it universally applicable. This inclusivity extends the reach and impact of our project, fostering the broader adoption of energy-efficient practices across diverse settings. Additionally, our approach yields benefit for both EV owners and smart building operators, as it concurrently reduces energy costs, optimizes energy consumption, and alleviates the overall strain on the grid. In essence, our research signifies a substantial leap towards sustainable and cost-effective energy management in commercial smart buildings, offering a solution that harmonizes the interests of all stakeholders.

4 System Design

The primary objective of the system is to seamlessly integrate EVs with commercial buildings while optimizing energy consumption within these structures. This integration is achieved without compromising the comfort and essential requirements of the building's occupants while also providing significant benefits to EV owners. To attain these goals, the system formulates a complex planning problem that incorporates critical data related to the building environment, EV characteristics, and day-ahead pricing information. Leveraging advanced temporal planning techniques, the system then generates a comprehensive plan that optimizes energy utilization by capitalizing on available resources and anticipating demand patterns. As a result, the system ensures the efficient and dependable operation of the building's energy infrastructure, meeting the occupants' comfort and functional needs, while concurrently enabling EV owners to charge their vehicles during periods of lower energy demand and cost, offering compelling incentives.

Within this chapter, we delve into two pivotal sub-domains of system design: the evaluation of commercial building loads and architectural design considerations. The process of designing a commercial building's system involves a multifaceted assessment of the various loads it will encounter, encompassing aspects like lighting, Heating, Ventilation, and Air Conditioning (HVAC), and electrical loads. Profound comprehension of these loads is pivotal for creating a system that excels in efficiency, cost-effectiveness, and alignment with the occupants' requirements.

Concurrently, architectural design plays an equally indispensable role, as it furnishes a visual representation of the system's components and delineates their interactions. This architectural diagram serves as a vital tool to ensure the comprehensive consideration of all facets of the system, spanning hardware and software components, network connections, and data flow. By embarking on a comprehensive exploration of these sub-disciplines, we aim to gain a profound insight into the intricacies of the system design process, highlighting the imperative nature of a holistic approach that encompasses every facet of system design. Let us now embark on an in-depth examination of these topics.

4.1 System Architecture

The system architecture serves as the backbone of any system, dictating its performance and functionality. It meticulously delineates the distinct components within the system and elucidates their interplay, all converging toward the realization of the intended objectives. Within the scope of our project, the system architecture assumes paramount significance, facilitating both efficient energy management within commercial buildings and the seamless and cost-effective charging of EVs, ensuring tangible benefits for both EV owners and the commercial building, is a pivotal aspect of our system's architecture. In this section, we embark on an exploration of our system's architecture diagram, unraveling its inner workings in the pursuit of our overarching goal.

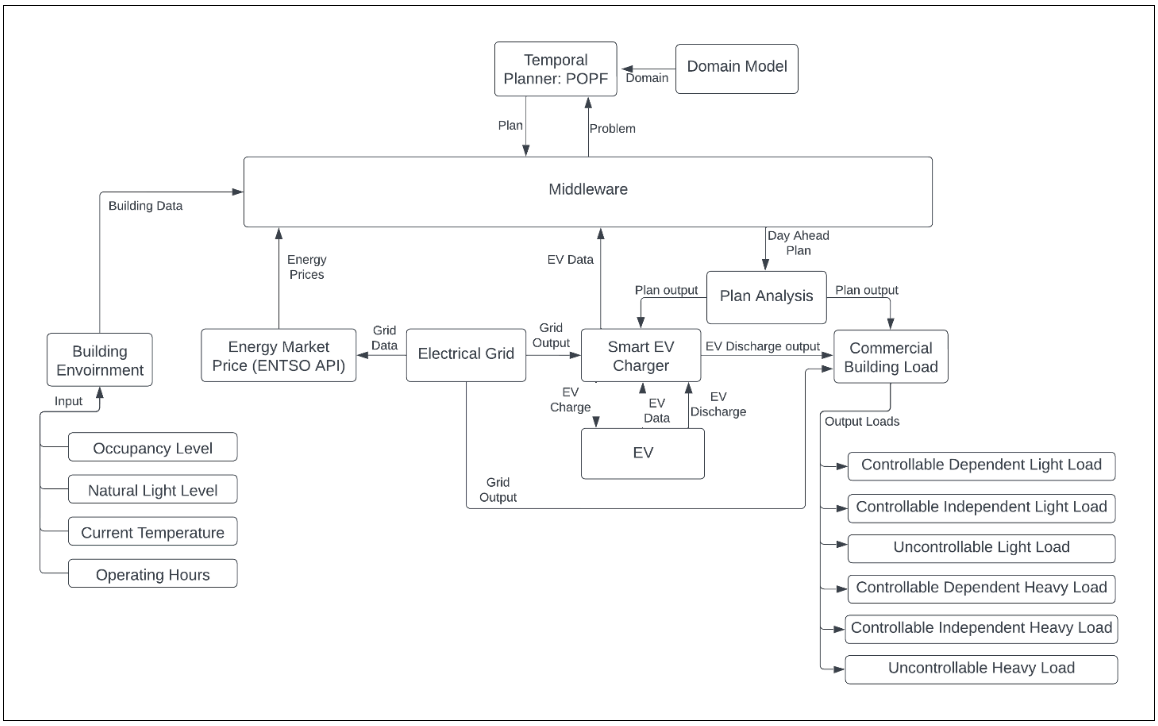

Figure 4.1: Overview of the Architecture Design

We have designed a comprehensive system architecture in Figure 4.1 that outlines the main components and their interactions. The architecture comprises the following components:

4.1.1 Building Environment

Within our system architecture, the "Building Environment"component stands as a cornerstone, responsible for gathering and managing essential data pertaining to the commercial building's environment. This critical component collects real-time information, including occupancy levels, outdoor light conditions, operating hours, and indoor temperature. These data points play a central role in the optimization of energy consumption, striking a balance between energy efficiency and occupant comfort. Subsequently, this data is seamlessly passed to the middle layer of our system.

4.1.2 Energy Market Prices

The component Energy Market Prices is responsible for sourcing hourly energy price data from the ENTSO API, which provides real-time pricing information specific to the German grid station. These real-time price figures, extracted via a REST API, hold paramount importance as they serve as the primary determinant influencing the decision-making process within our system. Subsequently, this vital energy price data is channeled to the middleware.

4.1.3 Middleware

Central to our system architecture is the indispensable "Middleware"component, which serves as the linchpin for seamless communication and integration. This pivotal element plays a multifaceted role in orchestrating the various components of our system. It acts as a bridge, adeptly integrating web services and APIs, such as the Energy Market Prices and Building Environment data, into the existing IT infrastructure. Additionally, it serves as a conduit for the influx of real-time EV data from the Smart EV Charger, consolidating this wealth of information into a comprehensive problem file. Equally vital, the Middleware efficiently manages the distribution of plans generated by the planner to the relevant components, ensuring a synchronized flow of data and instructions. In essence, the Middleware is the nerve center of our system, facilitating seamless communication and coordination among all interconnected components, thereby optimizing energy management in commercial buildings and enabling efficient EV integration.

4.1.4 Electrical Grid

This grid station supplies electricity to the Smart EV Charger and the loads in the Commercial Building. It serves as the primary source of electrical power. Additionally, the ENTSO API retrieves real-time energy prices from the grid station, measured in EUR per Megawatt-hour (MWh).

4.1.5 Plan analysis

Plan Analysis component acts like a traffic conductor, making sure that the instructions are carried out smoothly by directing them to the right places—the Smart EV Charger and the loads in the commercial building. This seamless execution of the plan is essential for achieving our goal of optimizing energy usage and ensuring efficient charging of electric vehicles while benefiting both EV owners and commercial buildings.

4.1.6 Smart EV Charger

This intelligent charger takes center stage when it comes to connecting EVs with the smart building infrastructure. When an EV is plugged into this charger, it retrieves vital information from the vehicle. This EV data includes details like the time of connection, the expected time of disconnection, the current SOC of the EV's battery, the daily driving range, and the average daily distance covered by the EV.

Using this information, the Smart EV Charger goes a step further by determining SOC threshold limits and establishing priorities for each vehicle. These priorities are crucial in managing the charging and discharging schedules effectively.

The EV data, along with the established priorities, is then passed on to the middleware, where it becomes an integral part of the decision-making process. The middleware utilizes this information, along with data from other system components, to generate a comprehensive plan. This plan specifies the optimal times and intensities for charging or discharging each EV.

Once the plan is ready, it is received by the Smart EV Charger from the Plan Analysis component. The charger takes these instructions and puts them into action. It ensures that each EV is charged or discharged according to the plan, making the entire process seamless and efficient.

In essence, the Smart EV Charger acts as the bridge between electric vehicles and the smart building, ensuring that EVs are charged in a way that benefits both the vehicle owners and the commercial building, while also considering factors like SOC and daily driving patterns. This integration enhances energy management and cost optimization in the smart building environment.

4.1.7 Commercial Building Loads

Let's delve into the "Commercial Building Loads"component, a vital part of our system that plays a significant role in optimizing energy consumption within commercial buildings.

In our system, the Commercial Building Loads component acts as the final destination for the plan generated by the POPF planner. This plan is a comprehensive road map that encompasses various aspects, including DSM, EV schedules, and the control of energy consumption from all the building's loads. Its primary objective is to achieve substantial reductions in energy costs while maintaining the highest level of functionality and comfort for building occupants. The detail of building loads is defined in next section 4.2.

The plan, derived from careful consideration of multiple factors, serves as a guideline for orchestrating energy-related activities within the building. It outlines when to draw power from the electrical grid, when to initiate EV charging sessions, and how to distribute energy efficiently among the various building loads.

By following this plan, the system ensures that energy is provided to the building precisely when occupants require it, meeting their needs without compromise. Simultaneously, it intelligently leverages the energy stored in EVs and applies DSM strategies to optimize energy utilization and minimize costs

4.1.8 Temporal Planner and Domain Model

The "Temporal Planner" and "Domain Modelïs a critical component in our system architecture. Temporal planner starts by taking domain and problem files as input. These files contain information about the building environment data, EV data and Energy Market Prices.

Using planner algorithms like POPF, the Temporal Planner creates plans tailored to the environment's unique characteristics. These plans optimize energy consumption, considering building data, EV details, and energy prices.

The generated plans are sent to the middleware for communication and then to the Plan Analysis component for execution.

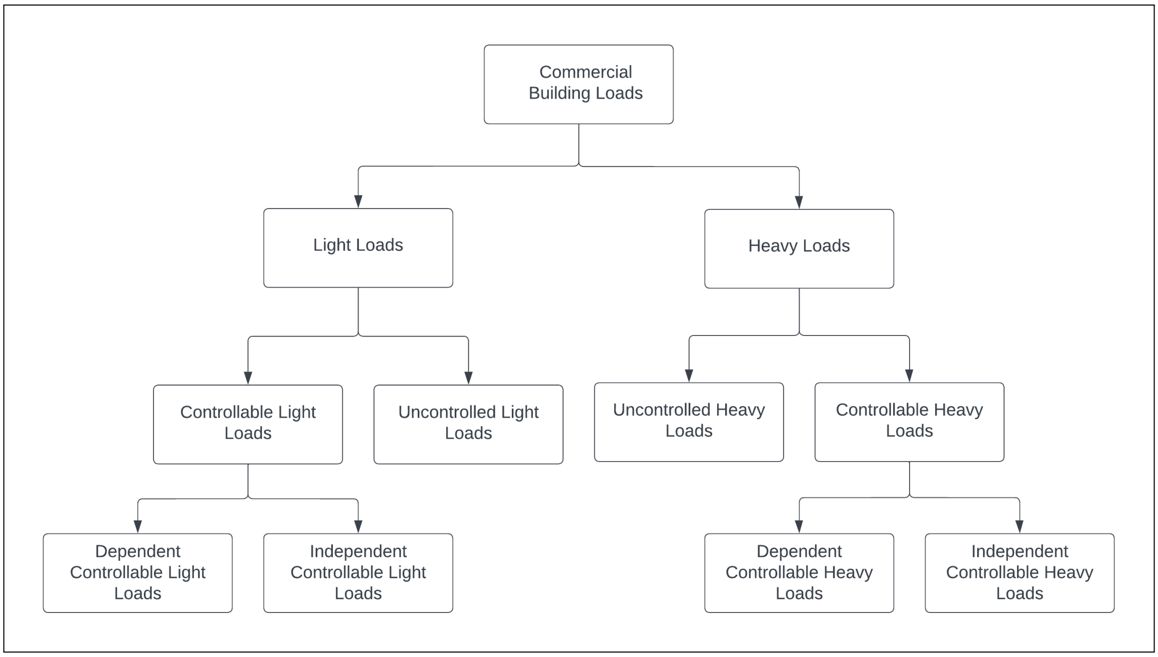

Figure 4.2: Commercial Building Electrical Loads

4.2 Commercial Building Loads

The various energy-consuming systems that are present in a building are referred to as loads in the context of smart commercial buildings. According to Figure 4.2., there are six main types of these loads. When designing an energy-efficient smart building, each of these loads must be taken into account.

The various loads that may be present in a commercial building are depicted in Figure 4.2. below. It's important to remember that these loads are generic in nature and can be found in the majority of commercial buildings rather than being specific to any one type of building. As a result, a broader approach is taken when designing an energy-efficient smart building.

In this section, we'll go into more detail about each of these loads and look at some energy-saving techniques.

There are mainly 2 types of loads in the building, Heavy Loads and Light Loads. These can be further decomposed into controllable and uncontrollable loads. Controllable loads can be further decomposed into Dependent and Independent loads.

4.2.1 Light Electrical Loads

Light Electrical Loads in commercial buildings are power-consuming gadgets that use relatively little electricity and typically don't produce a lot of heat. Plug-in devices like computers, printers, and charging stations make up the majority of these loads. Energy efficiency in commercial settings must be achieved through efficient management of these Light Loads.

4.2.2 Heavy Electrical Loads

In commercial buildings, heavy electrical loads are frequently related to the operation of large mechanical and electrical systems. These include elevators, data centers, HVAC systems, cooking equipment like ovens and stoves, and other sizable machinery. These High-Energy Loads use a lot more energy than Light Loads do, which has a big impact on a building's overall energy efficiency. For instance, the energy consumption of a building can be up to 50% due to the HVAC systems alone, while up to 20% can be attributed to lighting. In order to improve a building's energy efficiency, it is essential to reduce the power consumption of High-Energy Loads.

4.2.3 Controllable Loads

Controllable Loads are those in commercial buildings that can be adjusted in accordance with the cost of energy at the time and the environmental conditions inside the building. These are loads that can be either shut off or have their power consumption controlled in accordance with current energy prices and building requirements. DSM strategies, which are effective in managing these loads, can result in significant energy and cost savings. In our project, examples of Heavy Controllable Loads were HVAC systems and dishwashers, while examples of Light Controllable Loads were standard lights and situation-specific lights.

4.2.4 Uncontrollable Loads

Uncontrollable Loads are those that are solely under the control of the building's occupants and are not subject to building management. They could be Low or High Energy Loads. Electrical outlets for coffee makers, TVs, and printers are included in our project's list of light Uncontrollable Loads because they are always available for use by residents. Elevators and other appliances like ovens could be considered High-Energy Uncontrollable Loads. Strategies for DSM for these kinds of loads are covered in detail in the next chapter.

4.2.5 Dependent Controllable Loads

Electrical loads in commercial buildings that can be changed but are heavily reliant on variables like energy costs, the number of occupants, natural lighting, and ambient temperature are referred to as Dependent Controllable Loads. Smart energy management of these loads requires a multifaceted strategy that takes into account all of these factors. Ordinary lighting systems were categorized as Dependent Controllable Light Loads in our study, while HVAC systems were categorized as Dependent Controllable Heavy Loads. Significant energy and cost savings can be made by using intelligent controls and analytics without compromising occupant comfort.

4.2.6 Independent Controllable Loads

Electrical loads known as Independent Controllable Loads are those whose use in a commercial building is solely determined by the cost of energy at the time, without taking environmental considerations into account. In order to reduce costs and maximize energy consumption, these loads can be controlled solely based on current energy prices. For instance, situation-specific lights can be turned on or off solely based on energy costs for Independent Controllable Light Loads. Likewise, large appliances like dishwashers can be set to run only when energy costs are low. Building managers can significantly reduce energy costs by effectively managing these Independent Controllable Loads.

5 System Implementation

In Chapter 4, we outlined the comprehensive system architecture, setting the stage for the practical realization of our project. Chapter 5 delves into the intricate details of our system's implementation, providing a comprehensive account of the steps taken to transform our conceptual framework into a functional reality. This chapter serves as a road map, guiding readers through the journey from design to execution.

We embark on this journey by elucidating the key phases of the implementation process. Furthermore, we candidly address the challenges that arose during implementation and elucidate the strategies deployed to surmount them. Our aim is to provide an unvarnished account of the development journey, offering insights into the trials and triumphs of our project.

To enhance clarity, we include a visual aid in the form of a block diagram (Figure 5.1) that encapsulates the methodology employed throughout this thesis. This diagram serves as a valuable reference point, offering a clear and concise overview of our implementation process. As we delve into the specifics of each phase, the block diagram will serve as a navigational beacon, illuminating the path we traversed to achieve our objectives.

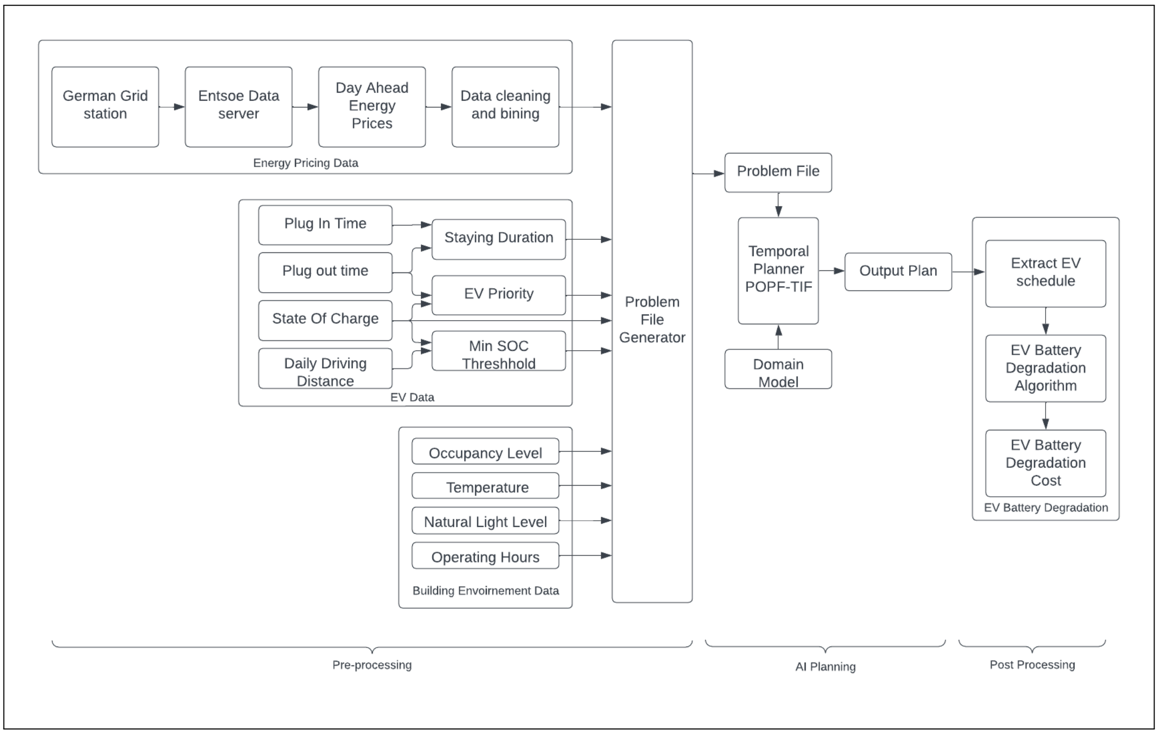

Figure 5.1: System Block Diagram

5.1 Pre-processing

In the initial stage of system implementation, we prioritized pre-processing, a critical phase aimed at refining our data inputs for further analysis. This phase primarily involved the acquisition of German Energy Market Prices, followed by extensive data filtration and binning procedures to extract more insightful data. Additionally, we procured essential EV data, which becomes accessible upon EV connection to the Smart Charger. This data serves as a fundamental element in our endeavor to seamlessly integrate electric vehicles into smart building operations. To enhance data relevance, we conducted comprehensive calculations to extract key insights. Furthermore, environmental data collection was integrated into the process to provide essential inputs for generating a problem file. This chapter delves into the intricacies of the pre-processing phase, shedding light on the tools and methodologies employed to procure, refine, and analyze the data effectively.

5.1.1 Energy Pricing Data

Our data collection process for energy pricing involved accessing the European Network of Transmission System Operators for Electricity (ENTSO-E) through their Representational State Transfer (REST) API. ENTSO-E is responsible for overseeing the secure and efficient operation of the electrical power transmission system in Europe, and it plays a pivotal role in data exchange among European Transmission System Operators (TSOs) and the development of a common data exchange platform for the European electricity market [Ent]. To retrieve energy prices from the ENTSO API, we utilized the HTTP GET method and submitted a request to the API endpoint. This request included essential parameters such as the API key, start date, end date, and market area, enabling us to specify the desired data for retrieval.

To streamline this data retrieval process, we developed a Python script that automates the interaction with the ENTSO API. The script accepts the date for which energy market prices are needed and sends the corresponding request to the ENTSO server. The API responds with a JSON file containing the requested data, particularly the hourly energy prices in EUR/MWh. This automated approach facilitated efficient and up-to-date data acquisition, crucial for our project's accuracy and reliability.

After acquiring the energy prices, the subsequent step involved data refinement and cleansing. We performed data filtration to extract prices at regular 60-minute intervals throughout a 24-hour period. Following data cleansing, we categorized the prices into three distinct groups: high energy prices, nominal energy prices, and low energy prices. This categorization aimed to cluster prices with similar characteristics, simplifying data analysis and interpretation. The binning process entailed dividing the prices into various ranges based on their values.

High energy prices were defined as prices surpassing a predetermined threshold value, determined based on historical price trends in the region. Nominal energy prices encompassed prices falling within a specified range, neither excessively high nor low. Lastly, low energy prices were identified as prices falling below a predefined threshold.

By employing this categorization method, we effectively associated price levels with each hour of the day within the problem file using Temporal Imprecision Factors (TIFs). This approach empowered us to make data-driven decisions considering the price range.

5.1.2 EV Data

EV data constitutes a vital element in our system, capturing crucial information about EVs connected to the Smart Charger. When an EV owner plugs their vehicle into the charging station, this data is extracted from the EV before the battery charging process commences. The EV data plays a pivotal role in determining the rate and timing of the vehicle's charging or discharging cycle.

This information is sourced from two distinct channels: directly from the EV's Electronic Control Unit (ECU) and from inputs provided by the EV owner upon plugging in the vehicle. Modern EVs exhibit a high degree of intelligence and communicate with charging stations to optimize the charging process. Certain data, however, necessitates manual input by the EV owner at the time of plugging in.

The amalgamation of this data is a critical step in our problem file generation process, enabling seamless integration with building energy consumption, energy market factors, and occupant needs. The pertinent variables within EV data encompass Plugin Time, Plug out Time, Duration of Stay, Daily Driving Distance, EV Priority, and Minimum State of Charge (Min SOC). These variables are elaborated upon below.

All the EV Data variables in the problem file are integrated with TIFs from Temporal Planning. This integration is crucial because these variables are highly time-sensitive and undergo changes as time progresses. TIFs enable us to dynamically adjust and update these variables based on the evolving conditions and requirements of each plugged-in EV. By utilizing TIFs, we ensure that our system can effectively manage and optimize the charging and discharging processes in real-time, responding to the dynamic nature of EV operations and energy market conditions.

EV Plugin Time

The EV Plugin Time denotes the moment when the EV owner connects their vehicle to the charger. It serves as a reference point for tracking the duration of the EV's presence during a given day. In our project, we manually input this value, assuming that the EV is plugged in at the specified time, although ideally, this information should be updated automatically by the EV Charger itself.

EV Plug out Time

The EV Plug out Time represents the moment when the EV owner intends to unplug their vehicle from the charger. It is a variable provided by the owner when initially plugging in the EV. The primary purpose of this variable is to inform the system about the availability duration of the vehicle. This information enables the system to assign priority to the EV and regulate its charging and discharging rates based on building environment data and Energy Market Factors.

EV Duration

Upon receiving information about the EV plugin and plugout times, the Smart EV charger performs a subtraction operation to determine the precise duration for which the EV remains connected to the charger.

EV SOC

The State of Charge (SOC) of the EV batteries is obtained from the EV as soon as it is plugged in. SOC represents the battery's charge level as a percentage, indicating how much of the battery's capacity is currently charged. For instance, if the SOC is 40%, it signifies that the battery is 40% charged and 60% empty. This SOC information, along with the EV's duration of stay, is crucial in determining the required charging time to reach a desired battery threshold. It allows us to optimize the charging process while considering factors like energy market conditions and the building's occupants' needs.

Daily driving Distance

The "Daily Driving Distance"variable represents the average distance an EV travels in a day. This information is provided by the EV itself when it is plugged in for charging. Knowing the daily driving distance is essential because it helps determine the daily energy requirements for the EV. By understanding how far the EV typically travels each day, we can ensure that the EV has sufficient SOC to meet its daily driving needs. In our project, this variable is manually inputted, as we do not have access to an actual EV for real-time data retrieval.

EV Min SOC

This variable specifies the minimum SOC that the EV should maintain at all times for emergency situations. In the event of an emergency where the owner needs to access the EV before the scheduled plug-out time, it is crucial that the EV has a minimum SOC threshold to ensure it can be driven safely. If the EV is already plugged in with an SOC below the specified minimum threshold, it will be charged with the highest priority, regardless of Energy Market Factors and Building Environment conditions, to ensure it meets the minimum SOC requirement.

The minimum SOC requirement, as specified in reference [NB], dictates that the EV should maintain a minimum SOC of at least 25%. This ensures that in emergency situations, the EV always has a sufficient charge level to be operational and ready for immediate use.

EV priority

The EV priority variable is of paramount importance in our system. It is calculated based on various EV data, including the EV's duration, daily driving distance, SOC, and minimum SOC requirements. This variable assigns a priority level to each plugged-in EV individually. Notably, the priority is dynamic and updates over time. As an EV's plug-out time approaches, its priority increases. Higher-priority EVs are given precedence in charging and discharging operations, ensuring they are fully charged by the time of plug-out. Conversely, EVs with lower priority may experience delayed charging if Energy Market Factors and building environmental data do not align favorably with meeting occupants' needs. To manage EV priorities throughout the day, we employ TIFs in the problem file, allowing us to specify priority levels at different time intervals.

5.1.3 Building Environment Data

Building environment information includes a variety of environmental factors that can affect how much energy a building use. In this project, we modeled energy consumption in a commercial setting by taking into account important variables like occupancy, the current temperature, the amount of natural light, and operating hours. Our strategy makes certain assumptions about these variables and presents a promising way to save money and energy. We go into more detail on each of these elements below.

Occupancy

The number of people occupying a building at any given time is known as occupancy. This factor has a significant impact on energy use because maintaining indoor comfort for more occupants typically requires higher energy costs. Based on varying occupancy levels at various times of the day, we have modelled energy consumption. The impact of various occupancy levels on energy costs will be covered in more detail in the following chapter.

In our project, while it would be more accurate to model energy consumption based on the fluctuating number of people in the building at different times, doing so would require the use of TIFs, adding considerable complexity to the problem. Given the limitations of our planning algorithms in efficiently solving such complex problems, we have opted for a simpler approach using TILs. TILs allow us to segment the day into specific periods when the building is occupied or unoccupied, thus providing a more computationally feasible way to adjust energy systems like HVAC and lighting based on occupancy, while still maintaining reasonable accuracy in our energy consumption models.

Current Temperature

The term "current temperature"refers to the ambient temperature inside a building that is influenced by the weather outside and its HVAC system. Energy use is directly impacted by the temperature inside the building. We have assumed that we are in the winter season which means that the indoor temperatures must typically be kept higher than those outside. The system receives this information about the current temperature and works to maintain an indoor climate within the comfortable range. This directly impacts the energy costs. The details of its implementation will be discussed further in the next section on the domain file.

We assume typical indoor winter temperatures range from 23°C to 26°C during the day and 17°C to 20°C at night, in accordance with a 2023 study by De Carli et al [DO]. The heating and cooling systems in commercial buildings use these temperatures as a standard reference. The temperature of the building at night during winter is estimated to be around 18°C. This temperature range is considered comfortable for most people and is commonly used as a reference for heating and cooling systems in commercial buildings [DO].

Natural Light Level

Natural light level is a significant environmental factor that affects a building's energy use, much like occupancy and the outside temperature. The amount of daylight that enters a building from the outside is referred to as the natural light level. The use of the building's interior lighting systems may be influenced by the amount of natural light. Energy consumption can be decreased while preserving a comfortable indoor environment by adjusting the use of artificial lighting in response to the level of natural light. We made an assumption about the amount of natural light outside the building for this project, and the next chapter about evaluation, will assess its effects on energy usage.

Operating Hours

Operating hours, or the time when the building is occupied, can have a big impact on how much energy is used. We can more accurately model the energy consumption and find areas for cost savings if the operating hours are set to correspond to the typical usage patterns of the building.

Our project's operating hours have been set at 08:00 to 20:00, which is a standard schedule for many commercial structures. This enables us to simulate the energy usage of a typical commercial building and assess the potential for energy optimization using this schedule.

Overall, accurate modeling and prediction of energy consumption, integration of EVs, and cost-optimization of energy use in commercial buildings are all made possible by building environment data.

5.1.4 Problem file generator

In our system implementation, the Problem File Generator assumes a pivotal role. This Python script acts as a crucial bridge between various data sources and the AI planner, facilitating the creation of a problem file in PDDL format. The input data for this generator comprises Energy Market Factors from ENTSO API, EV data retrieved from the Smart EV Charger, and building environmental data. The generator processes this data, including the variables mentioned earlier, to create a problem file rich with logical constraints. These constraints serve as the foundation for the AI planner's decision-making process.

The generated problem file, alongside the domain file, is then handed over to the POPF planner. The AI planner utilizes the information within these files to produce an optimized plan, detailing the energy consumption and EV charging schedule for the building. The plan is subsequently saved in a new file format with a ".plan ëxtension.

It's worth noting that we encountered challenges with the POPF-TIF planner, particularly an increase in the search state space due to the numerous variables incorporated as TIFs in the problem file. To address this issue, we adopted a pragmatic approach. We divided the problem file into two parts. The first problem file was generated and provided to the planner, along with the domain file, for initial execution. Once the plan was generated, it served as input for the Problem File Generator script. This script updated the input values based on plan 1, leading to the creation of a new problem file, referred to as problem file 2. problem file 2 underwent the same execution process. In the end, both plan 1 and plan 2 were merged to form a comprehensive plan covering the entire day, effectively addressing the challenges posed by the planner.

This process is explained below under the section of Problem file.

5.2 AI Planning Model

We will get into every aspect of our planning model, which forms the foundation of the accomplishment of our project, in this section. We are able to accomplish our main goal of optimizing building energy consumption while seamlessly integrating EVs with smart building systems thanks in large part to the planning model. We'll give a thorough rundown of all the technical details, features, and components that make up this model. It is crucial to realize that the planner, domain file, and problem file, along with their harmonious interaction, are how our planning model functions. Each of these elements is essential to the creation of the building's highly effective energy consumption plans. The functions of each component will be carefully examined in the sections that follow.

5.2.1 Planner POPF-TIF

No existing planner is capable of tackling the difficult task of combining temporal planning, TIFs, and trajectory constraints effectively. TIFs can, however, be combined into features that some temporal planners can control. The temporal extensions of the PMT architecture outlined by Gregory et al. in [GLFB12] are demonstrated by POPF-TIF. This makes it possible to time planned actions in relation to numerical events, which is currently a cutting-edge feature in the PDDL's temporal planning sub-area. Although it is not formally included in any PDDL language and is not used in generic PDDL planners, this feature is very helpful in real-world applications.

An extension of the original POPF 2, POPF-TIF supplies a robust framework for both temporal and metric planning [CCFL10]. It boasts the capability to preserve a semi-ordered sequence of actions within an evolving plan while also administering deadlines via TILs. The framework efficiently incorporates both TILs and TIFs as specialized actions that are executed at specified junctures [CCFL10], [CCFL11]. A distinguishing attribute of this planner is its adeptness at identifying 'compression-safe' actions—durative actions that can be encapsulated into a singular moment and later attributed to their time span [CFLS08].

Additionally, POPF-TIF is designed to enable coordinated network-wide actions, eschewing inefficient delay-based communication systems. It consistently outperforms reactive strategies by anticipating future demand and production patterns preemptively assessing future demand and production patterns, it consistently outperforms reactive strategies [Pia]. The planner allows for änytime planning,"which means it keeps looking for better results until the search terrain has been completely covered or an interruption happens. In situations where optimal solutions might be compromised by time constraints, special flags like -n and -tx can be used to activate anytime search and set time limitations, respectively [Tho].

The POPF Planner is not just concerned with make-span minimization in the context of our particular problem; it also takes into account a variety of preferences [BCC12]. It enables, for instance, the assessment of energy-efficient cooling options, such as choosing natural ventilation over air conditioning to decrease energy use and increase energy efficacy.

POPF-TIF, however, is not without flaws. Due to the size of the planning search space, it might struggle with complex temporal requirements, lengthening the planning phase or producing less-than-ideal results [PC]. Performance bottlenecks can appear when handling domains with a high density of actions, making it more difficult for the planner to thoroughly explore every combination [CCCF]. Additionally, it is unable to take into account negative preconditions, which could reduce plan accuracy by increasing predicate counts. However, its advantages outweigh these shortcomings, making it a powerful tool that can handle TIFs and trajectory constraints for a variety of applications. We sincerely thank Chiara Piacentini for her expert guidance, which improved our understanding and application of the POPF-TIF planner. We sincerely thank her for contributing so much to making our project better.

5.2.2 Domain file

The domain file assumes a central role in our planning model, serving as a pivotal component that defines the actions, objects, and predicates essential for problem solving within the designated domain. It offers a structured representation of the problem domain, laying the foundation for generating coherent plans aimed at achieving predefined goals. The meticulous design of the domain file is of paramount importance, ensuring that the planner can effectively reason through the problem space and derive practical and optimal plans. In this section, we will delve into the specifics of our domain file's design, elucidating the rationale behind our modeling choices. We will also provide an in-depth explanation of the domain file's syntax and its various constituent elements.

In our project, the domain file encompasses the entirety of a commercial building's loads, taking into account the integration of EVs while considering all aspects of building, as detailed in Sections 4.1 and 4.2. The primary objective in designing this domain is to facilitate the management of loads, EV charging, and discharging activities on both weekdays and weekends. This is achieved by leveraging input data from Energy Market Factors, EV data, and environmental data. The overarching goal is to optimize energy utilization within the building, seamlessly integrating EVs with smart building loads, all while meticulously safeguarding the comfort and needs of building occupants and EV owners.

To enable efficient interaction between loads and Boolean variables, the domain file incorporates predicates capable of altering their states. To accommodate these predicates effectively within the POPF-TIF Planner, they are implemented in two versions: positive and negated. For example, predicates like (working-day) and (not working-day) illustrate this duality within the domain.

Moreover, within the domain, there exist predicates capable of state modification, presenting both affirmative and negated forms, supplementing the Boolean variables described previously. These predicates play a pivotal role in facilitating action execution once the corresponding durative-actions have been carried out. To represent input and output data in numerical terms, the domain incorporates numeric variables known as Functions. These variables are closely linked to the data obtained from all inputs, encompassing energy market prices, EV data, and environmental data. Their significance lies in the seamless integration of EVs with building loads, with a core objective of optimizing energy utilization and cost-efficiency. They empower the domain to determine the optimal values for each EV and building variable based on real-time system conditions. The inclusion of these variables equips the domain with a comprehensive understanding of the building's energy consumption patterns, thereby enabling the development of strategies to curtail energy usage during peak hours, minimize wastage, and schedule EV charging and discharging for energy optimization and cost reduction.

The domain file introduces durative actions with a fixed duration of 1 hour, encompassing a total of 24 such actions for each load to generate a comprehensive daily plan. Similarly, the domain incorporates durative actions for the charging and discharging of vehicles, contingent upon energy market dynamics and building load demand. This approach allows the planner to sequence actions effectively, optimizing the building's energy costs by executing actions in an optimal sequence throughout the day. In the subsequent sections, we will explore each durative action in detail, providing insights into their design within the domain file.

EV Durative Actions

The domain file incorporates a set of critical durative actions related to EVs, forming an integral part of the domain's structure. These actions are paramount in the integration of EVs with smart buildings, taking into account various factors such as Energy Market prices, building environmental data, and occupant requirements. All EV-related durative actions possess a uniform duration of 2 hours, with their outcomes either involving EV battery charging, idleness, or discharge at varying rates.

There are several numeric functions used in the domain file like energy price levels (high, nominal, or low), the priority assigned to the connected EV at the smart charger, the minimum threshold limit, and the current SOC of the EV's battery. The SOC is a numeric function that represents the amount of energy stored in the battery. It ranges from 0% to 100%, where 0% indicates that the battery is completely discharged, and 100% indicates that the battery is fully charged. In our domain file, we have defined a continuous numeric function that tracks the state of charge of the EV battery. The value of this function changes based on the battery's charging and discharging rate and the building's energy demand. The SOC function is crucial in ensuring that the battery is not overcharged or over-discharged, which can damage the battery's health and longevity.

EV priority, a dynamic numeric function incorporated into our EV durative actions, serves as a crucial determinant in optimizing the integration of electric vehicles with smart buildings. This dynamic priority value continuously evolves as the plugout time approaches. As an electric vehicle's departure time draws nearer, its priority escalates, granting it precedence in the charging and discharging processes. This dynamic adjustment ensures that EVs are effectively charged before their scheduled departure, promoting efficient energy utilization and meeting the needs of both occupants and EV owners. EV priority is a key element in our system, aligning energy consumption with real-time demands and operational requirements.

The EV discharging rate, a continuous numeric function within our system, plays a pivotal role in managing the discharge of electric vehicle batteries to fulfill the energy requirements of the building. This function dynamically adjusts the rate of discharge based on prevailing energy prices. When energy costs are elevated, signifying high energy prices, the EV discharging rate increases. This adjustment enables the efficient utilization of EV power to support the building's climate control and other operational needs during periods of costlier energy. By integrating this continuous numeric function into our domain file, we ensure that the system adapts in real-time to optimize energy consumption and minimize expenses, aligning with the overarching goals of our project.

EV Durative Actions
EV_Discharge_HighPrice_aboveMinCharge_High_Priority
EV_Discharge_HighPrice_aboveMinCharge_Low_Priotity
EV_Charge_HighPrice_BelowMinCharge_High_Priority
EV_Discharge_HighPrice_BelowMinCharge_Low_Priority
EV_Discharge_NominalPrice_aboveMinCharge_High_Priority
EV_Idle_NominalPrice_Low_Priority
EV_Charge_NominalPrice_BelowMinCharge_No_Priority
EV_Charge_LowPrice
EV_SOC_Full

Table 5.1: Durative Actions of EV

The domain file defines a total of 9 distinct durative actions for EVs, meticulously covering all conceivable scenarios, as summarized in Table 5.1.

Each action is formulated to be mutually exclusive, ensuring that only one action can be executed at any given time based on the prevailing conditions. To enforce this exclusivity, a predicate named ßpeaking EVäcts as a semaphore, enabling an action while disabling access to others. This mechanism guarantees that the actions do not overlap, aligning with the conditions specified, and contributing to the fulfillment of the planning problem's objectives.

The nomenclature of each EV action succinctly reflects the associated conditions and anticipated effects, be it charging, discharging, or idling. Every action is tied to specific conditions that must be met for its execution, ultimately driving the planning problem towards its goal.

It's worth noting that these EV actions operate independently of the building's operational status. This means that the EV charger functions even during holidays or building closures. This design choice accommodates scenarios where EVs remain connected to the charger over weekends, enabling the utilization of EV batteries for peak load management. By selling surplus energy to the grid during periods of high demand and purchasing energy at lower rates, this approach not only offers financial benefits but also contributes to grid stability.

The four primary conditions common to all EV actions include the prevailing energy price, EV priority, current EV SOC, and the minimum EV SOC required at plugout time. When energy prices are high, and the EV possesses sufficient charge while holding a lower priority, the EV is discharged, diverting energy to building loads to meet occupants' daily needs. During this period of elevated energy prices, a significant portion of the building's load is shifted to the EV, resulting in the highest discharge rate. However, this discharge rate remains above the minimum SOC threshold for emergency purposes. When EV priority increases, the EV is charged based on its priority, even in the presence of high energy prices, with the associated costs borne by the EV owner. High priority indicates that the plugout time is imminent, or the EV SOC has fallen below the threshold limit, leaving insufficient SOC for emergency use.

Indeed, within the context of high energy prices, the primary objective of the actions is to maximize the utilization of EV batteries. During these periods of elevated energy costs, the actions are designed to discharge EVs as extensively as possible. This approach serves a dual purpose:

optimizing energy consumption within the building and alleviating the strain on the grid. By efficiently distributing energy demands to EVs, the building can effectively manage its energy needs while also contributing to grid stability by reducing the immediate demand from the grid. This optimization aligns with the broader goals of cost savings, energy efficiency, and grid reliability.

In situations with nominal energy prices, the actions' behavior depends on various factors, including EV priority and the state of the EV's SOC relative to the minimum threshold. When an EV has low priority and a sufficient SOC for emergency purposes, it has the option to either discharge its stored energy to fulfill the building's energy demands or remain idle if the building's energy requirements are modest. In such cases, it does not prioritize charging, as it anticipates lower energy prices in the near future.

Conversely, when an EV possesses high priority or has an SOC below the minimum charging threshold, it will initiate the charging process. However, the charging rate is regulated to conserve energy, ensuring that it doesn't charge at the highest rate possible. This approach optimizes energy usage by considering the EV's priority and its minimum required SOC while also being mindful of energy cost savings.

PDDL code below illustrates the simplest form of an EV durative action, which is designed to operate during periods of low energy prices. In this scenario, the primary objective is to maximize energy intake from the grid by charging all connected EVs at the highest charging rate and speed feasible, without taking into account the priority or SOC of the individual EVs. This strategy aims to fully charge the EVs so that they can be effectively utilized at a later time when their priority increases and their stored energy is needed to support the building's energy requirements. Once the EVs have reached a full state of charge, the action labeled as ËV SOC Full ïs executed, signifying that the EVs are now fully charged and available for future utilization.

```
;;;___________________EV at Low Energy Prices_________________________;;;

(:durative-action EV_Charge_LowPrice
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (=(Energy_Tariff) 2))    ;; Low Price
    (at start (Speaking_EV))
    (at start (enable))
    (at start (EV_Time_In))
    (over all (<=(EV_SOC_Percentage)90))
    )
    :effect (and
           (at end (increase (EV_SOC_Percentage)(EV_charge_rate))) ;;battery charging
            (at end (increase (EV_frequency)time-lapse))
            (at start (not(Speaking_EV)))
            (at end(Speaking_EV))
            )
)
```

Ordinary Lights Durative Actions
Ordinary_Lights_HighPrice_Occupied_HighNaturalLight
Ordinary_Lights_HighPrice_Occupied_LowNaturalLight
Ordinary_Lights_HighPrice_NotOccupied_HighNaturalLight
Ordinary_Lights_HighPrice_NotOccupied_LowNaturalLight
Ordinary_Lights_NominalPrice_Occupied_HighNaturalLight
Ordinary_Lights_NominalPrice_Occupied_LowNaturalLight
Ordinary_Lights_NominalPrice_NotOccupied_HighNaturalLight
Ordinary_Lights_NominalPrice_NotOccupied_LowNaturalLight
Ordinary_Lights_LowPrice_Occupied_HighNaturalLight
Ordinary_Lights_LowPrice_Occupied_LowNaturalLight
Ordinary_Lights_LowPrice_NotOccupied_HighNaturalLight
Ordinary_Lights_LowPrice_NotOccupied_LowNaturalLight

Table 5.2: Durative Actions of Ordinary Lights

In summary, the EV durative actions within our domain file are meticulously designed to optimize energy usage while integrating electric vehicles with smart building operations. These actions consider various factors, including energy prices, EV priorities, current SOC, and minimum SOC requirements. By dynamically adjusting the charging and discharging rates of EVs based on these factors, our system ensures efficient utilization of available resources, minimizes energy costs, and maintains energy security for both the building and electric vehicle owners. These actions play a pivotal role in achieving our goal of seamlessly integrating EVs with smart buildings while prioritizing energy efficiency and occupant comfort.

Light Controllable Dependent Load

The Light Controllable Dependent Load is a class of load that uses little energy but is very reliant on data about EVs, the environment, and energy prices. We have decided to represent the building's standard lights as a Light Controllable Dependent Load in the domain file for our project. According to Table 5.2, there are six possible durative actions for this load type. It's crucial to remember that these tasks cannot be completed simultaneously because doing so would make it impossible to reduce energy costs.

The Light Controllable Dependent Load is a type of load that has low energy consumption and is highly dependent on environmental data and day ahead prices. In our project's domain file, we have chosen to represent the building's ordinary lights as a Light Controllable Dependent Load. This load type allows for six possible durative actions, as outlined in Table 5.1 . However, it's important to note that these actions cannot be performed simultaneously, as doing so would be ineffective in optimizing energy costs.

The specific environmental, energy price and EV conditions for which each of the durable actions for the Light Controllable Dependent Load is intended are reflected in their names. Every action has particular requirements that must be satisfied before it can be carried out. For instance, while a working day is a prerequisite for all actions, each action has different energy costs, natural light levels, occupancy requirements, and other EV variables that were discussed in the section above. The planner chooses the appropriate course of action that will satisfy these requirements and advance the goal.

Each action has particular effects on the level of light. The intensity level is affected by a number of variables, including energy costs and the amount of daylight. High light intensities are not required when energy costs are high and natural light levels are high. In addition, depending on the occupancy levels, the lights should be partially or completely turned off. The planner selects the action that best fits the current circumstances after carefully considering the effects specified under each individual action.

Take the action Ordinary_Lights_NominalPrice_NotOccupied_HighNaturalLightäs an example. This procedure is only carried out when energy costs are low, no one occupies the building during the day, and there is an abundance of natural light. The majority of the lights can be turned off, and the hallway lights' intensity can be decreased, saving money because the building is empty and has plenty of natural light.

Heavy Controllable Dependent Load

Despite having different conditions and outcomes, the Heavy Controllable Dependent Load is conceptually similar to the Light Controllable Dependent Load. The HVAC system has been selected as the Heavy Controllable Dependent Load for this project. The HVAC also has six potential actions that are named for the particular environmental conditions they are intended for, similar to the Light Controllable Dependent Load.

Several variables that are added as functions to the domain file are needed to model the HVAC. These factors include the building's current temperature and the ideal temperature range that guarantees the occupants' productivity is not jeopardized. The thermally comfortable temperature range of a room was determined using an energy optimization paper by taking into account variables like air temperature, mean radiant temperature, relative air velocity, humidity, activity level/metabolic rate, and clothing thermal resistance. According to the study's findings, the range of temperatures where people can be thermally comfortable is between 77.8°F (25.44°C) and 66.4°F (19.1°C) [Sha21]. Using this data, we set the domain file's numeric functions to have values of 19.1°C for the comfort minimum limit and 25.44°C for the comfort maximum limit. According to the numerical function of current-temp in the project, the building's current temperature in winter is 18°C. By adjusting its speed, the HVAC is intended to keep the temperature within a comfortable range. By doing this, it ensures the comfort of the occupants while optimizing energy usage and lowering energy costs.

A thorough list of HVAC system durative actions is provided in Table 5.3, which is based on the particular environmental factors, energy costs, and EV condition. The HVAC system is only supposed to run from 08:00 to 20:00, when the building is open for business. The occupancy level, energy tariff, the building's current temperature, and certain conditions like EV SOC, which enables the HVAC system to control its speed in accordance with the energy requirements, all affect the duration of each action. For instance, there is no need to turn on the HVAC system in order to maximize the cost during times of high energy prices if the building is already within the ideal temperature range. Similar to this, the HVAC system's speed is modified according to the demands of the surrounding environment. When energy prices are not high, lower speeds use less energy,

HVAC Durative Actions
hvac_Highprice_occupied_InTempRange
hvac_Highprice_occupied_NotIntempRange
hvac_Highprice_unoccupied_InTempRange
hvac_Highprice_unoccupied_NotInTempRange
hvac_Nominalprice_occupied_InTempRange
hvac_Nominalprice_occupied_NotIntempRange
hvac_Nominalprice_unoccupied_InTempRange
hvac_Nominalprice_unoccupied_NotInTempRange
hvac_Lowprice_occupied_InTempRange
hvac_Lowprice_occupied_NotIntempRange
hvac_Lowprice_unoccupied_InTempRange
hvac_Lowprice_unoccupied_NotInTempRange

Table 5.3: Durative Actions for HVAC

which is primarily used to maintain the temperature range. When the energy prices are high and we have enough charge available in EVs plugged in, we can also utilize EVs to meet the demand of the building.

Uncontrollable Loads

Uncontrollable loads are a class of load that the system is unable to control. The residents may require them at any time of the day. They can be either light or heavy loads, and the predicates Üncontrollable_LightLoads änd Üncontrollable_HeavyLoads äre used to represent them in the domain file. These loads solely depend on energy prices and are unaffected by environmental factors. There are three continuous actions for each load type that repeat during building operating hours, and they can only be turned on during those times. The outputs of these three actions, "HighPrice_Uncontrollable_Loads ","NominalPrice_Uncontrollable_Loads änd "LowPrice_Uncontrollable_Loads ßhow whether the loads would draw power from the grid or from EVs.

Both high and low uncontrollable loads are shifted to draw energy from EVs during peak hours when the cost of energy is highest. The EV SOC, EV duration of stay, EV priority level, and Min SOC threshold are EV factors that influence this shift. Light uncontrollable loads are transferred to the grid to use as little energy as possible if the load is too much for the EVs. Only if the battery's SOC is at its maximum and it won't be needed in the future would loads be transferred to EVs if the cost is nominal. On the basis of cost optimization for the building, the planner chooses which actions to carry out.

Controllable Independent Loads

In terms of dependency, Controllable Independent Loads are comparable to Uncontrollable Loads. Controllable Independent Loads are defined in our project as loads that can be turned on or off regardless of the external environment, but whose operation is entirely reliant on energy prices.

The dishwasher is an example of a Heavy Controllable Independent Load, and the placed lights are an example of a Light Controllable Independent Load. These loads have been divided into high and low loads.

We have used four predicates, two for each load type, to represent the on and off states for these loads in the domain file. Because POPF-TIF does not recognize negative preconditions, it is crucial to note that we had to define the on and off states of the loads explicitly. The following are the predicates:

(Controllable_Heavy_IndependentLoad_Dishwasher_ON)
(Controllable_Heavy_IndependentLoad_Dishwasher_OFF)
(controllable_light_Independentload_Situatedlights_ON)
(controllable_light_Independentload_Situatedlights_OFF)

To optimize the cost of the building, we have combined the controllable independent loads with the uncontrollable loads into three actions named:

"HighPrice_Uncontrollable_Loads_Controllable_Independent_Loads",
"NominalPrice_Uncontrollable_Loads_Controllable_Independent_Loads ",
"LowPrice_Uncontrollable_Loads_Controllable_Independent_Loads".

These actions are dependent on energy prices and are subject to the same restrictions and requirements as the uncontrollable loads.The planner would carry out the action that turns off the Controllable Independent Loads to reduce costs while keeping the Uncontrollable Loads on during peak hours when energy prices are high.

Out of Operating Hours

So far, our discussion has focused on the domain model concerning the building's active operational hours. In this segment, we shift our attention to energy optimization strategies employed during the building's non-operational periods, including weekends and public holidays when the facility is shut down. During these off-hours, all energy-consuming loads in the building are deactivated, save for what we've termed the Light Controllable Dependent Load. In our scenario, this primarily involves standard lighting fixtures. These essential lights, like those illuminating hallways, continue to function but at a diminished intensity, thereby minimizing energy consumption.

It's important to clarify that EVs are an exception in this framework, as their operational cycles are not bound by the building's working hours. In our model, EVs are scheduled to operate around the clock. The actions governing their charging and discharging are strategically designed to capitalize on fluctuating energy prices—charging batteries when energy rates are low and discharging them when rates are elevated. By doing so, the energy is sold back to the grid at a premium, effectively curtailing operational costs even during the weekends.

Envelope action

In AI planning scenarios, ensuring that the system adheres to a 24-hour operation cycle while also meeting specific constraints is crucial. This is where the concept of the 'Envelope Action' becomes integral. Serving as the inaugural action in the plan, the Envelope Action takes precedence over all subsequent actions, including TIFs. Its primary role is to dictate the operational boundaries for all subsequent actions, effectively ensuring they fall within the envelope's predefined constraints [Pia]. The action accomplishes this by laying down a conditional prerequisite that must be acknowledged by every other subsequent action, thereby preventing them from initiating prior to the envelope's öpeningänd exceeding its outlined limits [Pia].

One pivotal characteristic of the Envelope Action is its non-terminating nature until the problem's goals are fulfilled [Pia]. This ensures that each action in the plan has sufficient time to be executed and achieve its intended outcomes. This non-termination condition is upheld throughout the plan thanks to the monotonic properties of relaxed reachability, a feature that remains stable across the TRPG that originates from any state where this condition is already met [Pia].

In our specialized domain, the Envelope Action is active for a full 24-hour span and concludes with an 'at end' condition stating that the operational day has concluded, thereby terminating the envelope action. The action's constraining factors include the need to keep the ambient temperature within optimum upper and lower limits and to manage the EV charging and discharging cycles so that they remain compliant with the envelope's constraints throughout the entire 24-hour cycle. This ensures the system operates seamlessly within the set parameters for the entirety of the plan, aligning it with the ultimate goals of the planning exercise.

5.2.3 Problem file

The problem file serves as a critical element in our automated temporal planning system. It encapsulates the real-world environment, incorporating vital data related to energy market prices, EV parameters (such as SOC, Min SOC threshold, EV priority, daily driving distance, plugin and plugout times), and environmental data (including temperature, occupancy, natural light levels, and operating hours). This file comprises both the initial state, describing the initial status of predicates and numeric functions, and the defined goals that must be achieved. To account for the dynamic changes in state throughout the day, we employ TILs and TIFs within the problem file. These temporal constructs are essential for representing time in our planning domain, ensuring that plans remain valid across different time periods and adhere to the constraints outlined in the domain model.

Our problem files are automatically generated using the Python script "Problem File Generator.py."This script takes input data, including environmental information, EV data, and energy market prices, to construct the problem files. To address the limitations of the POPF-TIF planner discussed in Section 5.2.1, the generated problem file is divided into two parts: the first part covers the time from 00:00 to 15:00, and the second part spans from 15:00 to 24:00. This division mitigates the challenges associated with lengthy planning times and sub optimal solutions. Initially, problem file 1 is created by the script, considering the initial environmental and EV values for the first 15 hours of the day. Problem file 1 is then fed into the POPF planner, alongside the domain file, to generate plan 1. Subsequently, plan 1 serves as input for the Problem File Generator script, which processes the actions within the plan to update the values of predicates and numeric functions. Based on these updated values, problem file 2 is generated, encompassing the time frame from 15:00 to 24:00. Problem file 2 is once again provided to the planner, which computes plan 2. Finally, plan 1 and plan 2 are amalgamated to form a comprehensive plan for the entire day. This approach represents a compromise in domain and problem file design, aiming to enhance the efficiency and functionality of the planner.

```
;;;_________________________________EV_________________________________;;;

(speaking_EV)
(= (EV_frequency)0)

(at 8 (EV_Time_In))
(at 12 (EV_Time_In))

(at 14 (EV_Time_In))
(at 16 (EV_Time_In))
(at 20 (not(EV_Time_In)))
(at 22 (not(EV_Time_In)))

;;;________________________________EV variables________________________________;;;

(= (EV_discharge_rate_highprice)15)
(= (EV_Discharge_rate_nominalprice)5)
(= (EV_charge_rate_highPrice)10)
(= (EV_charge_rate_NominalPrice)15)
(= (EV_charge_rate_LowPrice)20)

(= (EV_SOC_Percentage)60)
(= (EV_Min_Charge_at_Time_Out)40)

;;;_________________________________EV Priority_________________________________;;;
;; 1 Low priority, 0 High priority ;;
(= (EV_Priority)1)
(at 8 (=(EV_Priority)1))
(at 12 (=(EV_Priority)1))

(at 14 (=(EV_Priority)0))
(at 16 (=(EV_Priority)0))
(at 20 (=(EV_Priority)0))
(at 22 (=(EV_Priority)0))
```

The code above serves as an illustrative example, demonstrating how EV predicates and numeric functions are configured within the problem file through the utilization of TILs and TIFs, respectively. Predicates, which can hold values of either true or false, employ TILs for value assignment, whereas numeric functions exclusively rely on TIFs. Let's delve into the specifics:

Predicates with TILs: Take the example of ËV_Time_In,ä predicate that can assume values of either true or false. When written as "(not(EV_Time_In)),ït can alternate between true and false throughout the day. The representation of time in this context is measured in hours. Predicates employing TILs exhibit temporal variability, allowing them to transition between states at different times.

Numeric Functions with TIFs: In contrast, numeric functions like ËV_Priorityäre assigned values at various points during the day using TIFs. These functions encompass a range of values that vary over time. TIFs play a crucial role in capturing this temporal nature. Numeric functions that employ TIFs are dynamic and subject to change as time progresses.

It's important to note that while TILs and TIFs are instrumental in providing temporal characteristics to certain variables within the problem file, not all EV variables are time-dependent. Some variables remain constant throughout the day and are not influenced by time-based fluctuations such as EV discharge and charge rates.

The Envelope Action stands as a pivotal element in the system's continuous operation over a 24-hour cycle, while meticulously adhering to the constraints specified within the defined envelope. It's imperative to emphasize that the successful execution of the Envelope Action hinges upon achieving the objectives delineated in the problem file. Importantly, these objectives can only be realized once the full 24-hour duration has transpired. Consequently, the ultimate aim of the problem file aligns with the outcomes of the Envelope Action, culminating upon the culmination of the entire 24-hour time frame. This orchestration ensures the smooth and synchronized functioning of the system, optimizing energy usage and other vital parameters throughout the day.

5.3 Output Full Day Plan

The POPF-TIF planner analyzes the problem and domain file mentioned above and determines the best plan for entire day that can optimize energy by integrating EVs with smart buildings without sacrificing the building environmental conditions for the occupants and benefiting EV owners. The Figure 5.2. below shows the full day plan.

5.4 Post-processing

This section delves specifically into the EV battery degradation factor that arises after the execution of the plan. As the plan is executed, it involves a series of actions to charge and discharge the EVs connected to the smart charger, which serves to facilitate the building by providing energy to meet its demand, reduce the energy cost, and share the grid load. While this is highly beneficial for the building and the grid, there's a trade-off to consider. The EV batteries, which act as the energy source, undergo discharge cycles, leading to gradual battery degradation. To incentivize EV owners to participate in this innovative V2B technology we've developed, we also need to provide compensation for the battery cost, contingent upon the extent of battery degradation.

The outcome of these actions can result in either charging or discharging the EV batteries at different rates, which is determined by factors such as energy market prices, building environment data, and the building's energy requirements. Using this information, the script performs calculations to

```
Number of literals: 23
; Cost: 14.003
; Time 1.72
0.003: (day_ahead_plan_24h)  [14.000]
0.004: (out_of_operating_hours_all_off_lightsreduced)  [4.000]
0.004: (battery_charge_low_price)  [2.000]
2.005: (battery_charge_low_price)  [2.000]
4.006: (battery_charge_low_price)  [2.000]
8.001: (ordinary_lights_dim_highprice_occupied_highnaturallight)  [2.000]
8.001: (hvac_highprice_occupied_intemprange)  [2.000]
8.001: (ev_discharge_highprice_abovemincharge_low_priotity)  [2.000]
8.001: (battery_discharge_highprice)  [2.000]
8.001: (uncontrollable_loads_controllable_independent_loads_highprice)  [2.000]
12.001: (hvac_nominalprice_occupied_intemprange)  [2.000]
12.002: (ev_idle_nominalprice_low_priority)  [2.000]
12.002: (battery_discharge_nominalprice)  [2.000]
12.002: (ordinary_lights_dim_nominalprice_occupied_highnaturallight)  [2.000]
12.002: (uncontrollable_loads_controllable_independent_loads_nominalprice)  [2.000]
14.001: (day_ahead_plan_24h)  [10.001]
14.002: (ev_charge_lowprice)  [2.000]
14.002: (battery_charge_low_price)  [2.000]
14.002: (ordinary_lights_lowprice_occupied_highnaturallight)  [2.000]
14.002: (hvac_lowprice_occupied_intemprange)  [2.000]
14.002: (uncontrollable_loads_controllable_independent_loads_lowprice)  [2.000]
16.003: (ev_charge_lowprice)  [2.000]
16.003: (battery_charge_low_price)  [2.000]
16.003: (ordinary_lights_lowprice_occupied_highnaturallight)  [2.000]
16.003: (hvac_lowprice_occupied_intemprange)  [2.000]
16.003: (uncontrollable_loads_controllable_independent_loads_lowprice)  [2.000]
20.001: (out_of_operating_hours_all_off_lightsreduced)  [4.000]
22.001: (battery_charge_low_price)  [2.000]
```

Figure 5.2: Full Day Plan

determine the extent to which the EV battery has been discharged, expressed in terms of the SOC percentage. This post-processing step allows us to assess the impact of the plan on the EV batteries and provides valuable insights into battery degradation and compensation

5.4.1 EV Battery Degradation Algorithm

Calculating battery degradation is a complex and multifaceted process that involves numerous factors and considerations. In the context of our project, where electric vehicle (EV) batteries are utilized to optimize energy consumption in commercial buildings, understanding and quantifying battery degradation is crucial. It not only impacts the performance and lifespan of EV batteries but also plays a pivotal role in compensating EV owners for their contribution to the project. To arrive at a comprehensive assessment of battery degradation and its associated cost, we leveraged insights from a case study involving Tesla Model S [Cri] to calculate the battery degradation factor and, consequently, the associated degradation cost. In the case study, the Tesla Model S was used as an example, and its lithium-ion battery pack with a capacity of 100 kWh was considered. It was observed that this battery pack could endure approximately 1500 charge cycles until it degraded to 80% of its original capacity, which equates to 80 kWh remaining. Tesla's recommendation was to change specific battery modules after this degradation threshold was reached, incurring a cost of $7000 for these replacements. To determine the cost of a single charge cycle, we used this information. If 1500 cycles cost $7000, then each individual charge cycle roughly amounted to $4.6. It's important to clarify what constitutes a single charge cycle: it represents the process of charging the battery from 0% to 100% and then discharging it back to 0%. Now, with this understanding, we were able to calculate the degradation cost based on how much of the battery was utilized. For instance, if we discharged 20% of a cycle in total, equivalent to 0.2 cycles, the total degradation cost would be 0.2 * $4.6, resulting in a degradation cost of $0.92 for the amount of battery utilized.

In this way, we were able to quantify the battery degradation cost incurred by utilizing the EV battery in our project, using a real-world case study as a basis for our calculations.

5.5 Summary

In summary, the system implementation comprises several key steps. It initiates with the pre-processing phase, involving the collection and organization of environmental data, EV data, and energy prices. Subsequently, problem and domain files are generated based on this data, and these files serve as inputs for the POPF-TIF planner. The planner's execution results in the creation of a comprehensive full-day plan, which outlines actions for energy optimization and smart building management. Post-processing of this plan is then performed to calculate the battery degradation cost associated with the V2B service. This cost assessment is essential to compensate EV owners for their contribution to the project. In essence, the system offers an efficient and effective solution for automating the planning process, achieving energy optimization, maintaining comfortable indoor environments, and providing benefits to EV owners, thereby fostering the integration of electric vehicles into smart building ecosystems.

6 Evaluation

6.1 Experimental design

In the Experimental Design section, we delve into the successful integration of EVs with smart building systems using Temporal Planning. However, a prominent challenge that emerged during implementation stemmed from the limitations of the POPF-TIF planner, as outlined in Section 5.2.1. Although POPF-TIF stands as a robust planner uniquely equipped to handle TIFs, it encounters difficulties when dealing with complex temporal constraints. This can lead to prolonged planning times and sub optimal solutions, particularly in scenarios involving a substantial number of actions within the domain [PC].

To address these issues stemming from the POPF-TIF planner, we made several strategic adjustments in the design of both the Domain and Problem files. In the Domain file, we refrained from utilizing disjunctive preconditions such as ÖRänd över all"conditions, while also avoiding the inclusion of self-overlap actions, which are challenging for the planner to interpret [Ede]. In the Problem file, we had to partition it into two segments—problem file 1 and problem file 2—due to concerns related to state space and the sheer volume of actions within the domain, as elucidated in Section 5.2.3.

Given these necessary adaptations to enhance the planner's efficiency and effectiveness, we have established an experimental design to comprehensively evaluate the performance of POPF-TIF. This experimental setup aims to specifically investigate the impact of various predicates and numeric functions on the planner's performance. By conducting these experiments, we seek to gain insights into how to optimize the planner's capabilities and ultimately achieve more efficient and effective integration of EVs with smart building systems.

In our experimental design, we have conducted a simulation encompassing a wide array of variables, each having a range of possible values. The primary objective of this simulation is to meticulously investigate how these variables impact the state space and state evaluation when the planner executes problem files containing these diverse values. These variables are drawn from both EV data and environmental data, with the energy tariff being directly obtained from the real-time ENTSO API, making it a constant factor that cannot be altered.

The variables included in this simulation are as follows:

EV State of Charge at the Time of Plugin

This variable represents the initial state of charge for EV batteries when they are plugged into the smart charger. By considering levels from 20% to 100%, we encompass a wide range of battery states. Lower initial states may require more charging, affecting both the charging duration and the potential for discharging to the building later.

EV Plugin Time and EV Plug Out Time

These parameters determine the duration of the EV's stay at the charging station. Our exploration covers durations from 2 hours to extended intervals, such as 16 hours or more. Longer stays may result in different charging and discharging patterns, impacting the building's energy usage and cost.

EV Driving Distance/Min Charge Limit SOC

This variable combines the daily driving distance of the EV and the minimum SOC required for safety or emergency purposes. The range spans from 20% to 100%, representing various driving distances and minimum charge thresholds. A lower SOC or a higher driving distance may necessitate more charging and affect the EV's availability for building energy support.

Building Occupancy

We have explored occupancy patterns in terms of hours, ranging from short durations of 2 hours to full-day occupancy scenarios. This variable influences the building's energy demand. Longer occupancy durations typically result in higher energy consumption, impacting the need for EV contribution.

Natural Light Outside the Building

This variable simulates variations in natural light availability, from 2 hours of daylight to extended periods, such as 16 hours or more. It is crucial for understanding how natural light affects indoor lighting and, subsequently, the building's electricity consumption.

Building Temperature (in Degrees Celsius)

Temperature settings have been considered at different levels, ranging from 18°C to 26°C. These values represent varying indoor climate conditions, which impact heating, ventilation, and air conditioning (HVAC) requirements and, consequently, energy usage.

Working Day

This parameter accounts for different working day scenarios, including full-day occupancy, half-day occupancy, and holidays. It affects the building's operational hours and energy demand patterns, reflecting the diverse needs of occupants on different days.

By simulating a broad spectrum of realistic values for each parameter, we obtain multiple sets of output plans, each corresponding to a unique combination of parameter values. This comprehensive approach empowers us to conduct in-depth analyses, scrutinizing the impact of parameter variations on the resulting plans, their time frames, associated costs, and overall system states. Through this experimentation, we aim to gain valuable insights into the intricate dynamics of our integrated EV and smart building system, allowing us to optimize its performance and efficiency.

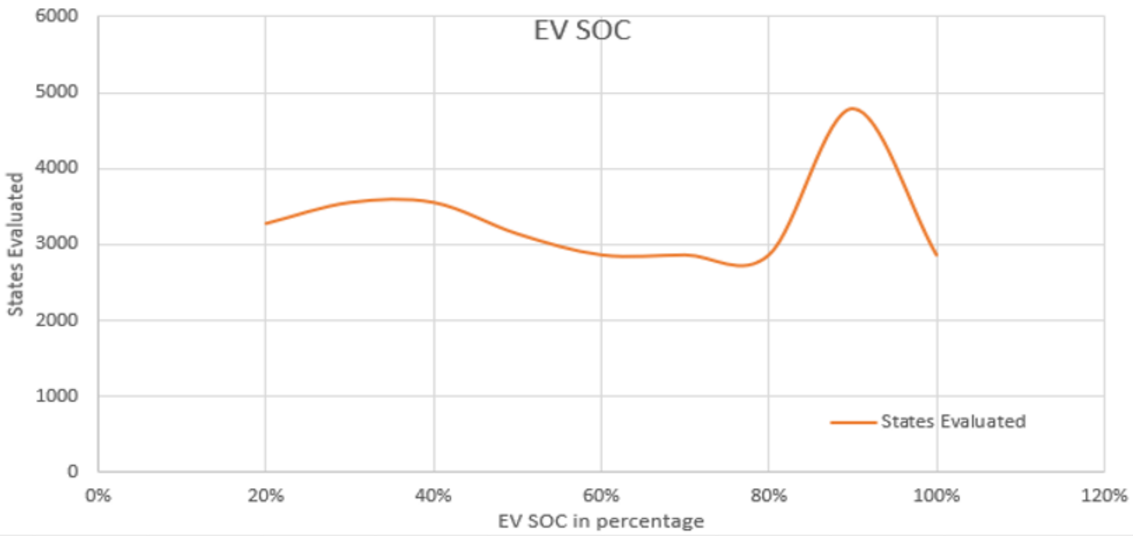

Figure 6.1: States Evaluated by simulating EV SOC

6.2 Results Analysis

In this section, we will analyze the results of our experimental design, where we explored the impact of various parameters and values on the performance of the POPF-TIF planner in the context of integrating EVs with smart buildings using temporal planning. The purpose of this analysis is to gain insights into how changes in these parameters affect the plans generated by the planner and how much states have been evaluated by the planner. We will go one by one through all the variables

EV State of Charge at the Time of Plugin

We have simulated numeric fluent "EV_SOC" with all the possible values from 20% to 100% keeping all the other environment data variables and EV data variables same to check the effect of changing this variable on computing the plan. How much time it takes to compute a plan and how much states are calculated upon simulating this variable.

Figure 6.1 illustrates how the EV SOC affects the performance of the planner. As we vary the initial SOC levels from 20% to 100%, we observe corresponding changes in the number of states evaluated by the planner. On average, around 3300 states are evaluated, with a peak of 4798 states when the EV SOC is set to 90%. The minimum states evaluated are observed at 2859 when the EV SOC is between 60% and 80%. The cost, representing the energy cost of the generated plans, remains relatively consistent across different SOC levels.

In Figure 6.2, the average time taken to compute the plan is 2.82 seconds, with a maximum of 3.71 seconds observed when the SOC is at 90%. This increased time can be attributed to the larger state space generated due to the higher SOC value.

EV Driving Distance/Minimum Charge Limit SOC

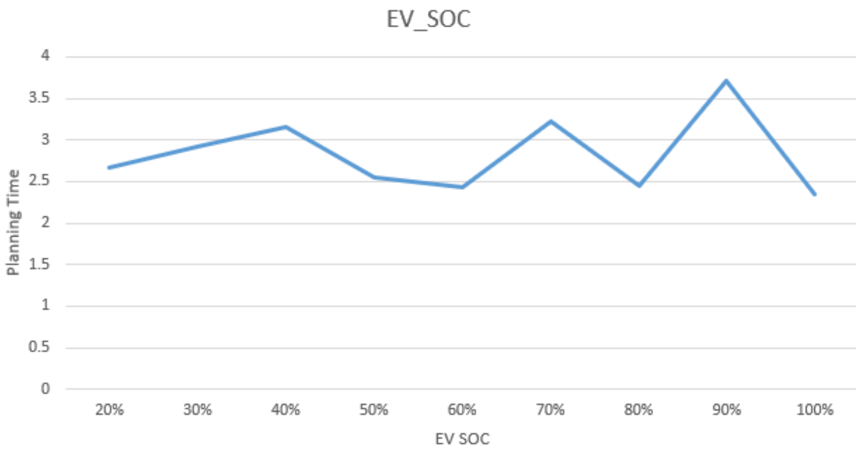

Figure 6.2: Planning Time upon simulating EV SOC

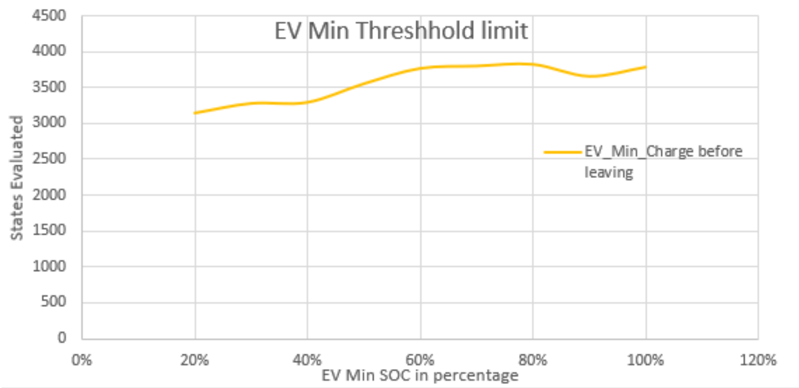

Figure 6.3: States Evaluated by simulating EV Minimum SOC Charge limit

Figure 6.3 presents the results pertaining to the ËV Min Charge"parameter. This parameter reflects the minimum charge level required for an EV before it can be discharged to support the building's energy demands. As we vary the EV Minimum Charge from 20% to 100%, we observe changes in the number of states evaluated, the energy cost, and the time taken for planning.

The number of states evaluated by the planner increases as the EV Min Charge requirement becomes more stringent. Specifically, when the EV Min Charge is set at 60% or higher, the number of states evaluated exceeds 3700, with a peak of 3830 states when the EV Min Charge is 80%.

In Figure 6.4, the time taken to compute the plan increases as the EV Min Charge requirement becomes more stringent. The average time is 2.96 seconds, with the maximum time of 3.38 seconds observed when the EV Min Charge is set to 80%. This indicates that the planner requires more computational resources to meet stricter EV Min Charge conditions.In Figure 6.2.4, the time taken to compute the plan increases as the EV Min Charge requirement becomes more stringent. The average time is 2.96 seconds, with the maximum time of 3.38 seconds observed when the EV Min Charge is set to 80%. This indicates that the planner requires more computational resources to meet stricter EV Min Charge conditions.

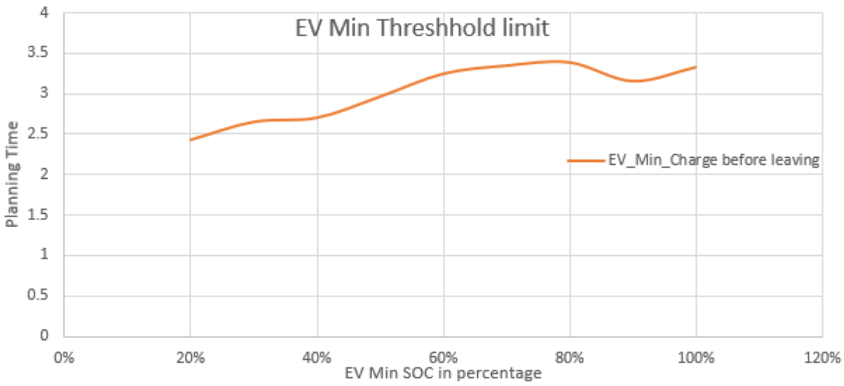

Figure 6.4: Planning Time by simulating EV Minimum SOC Charge limit

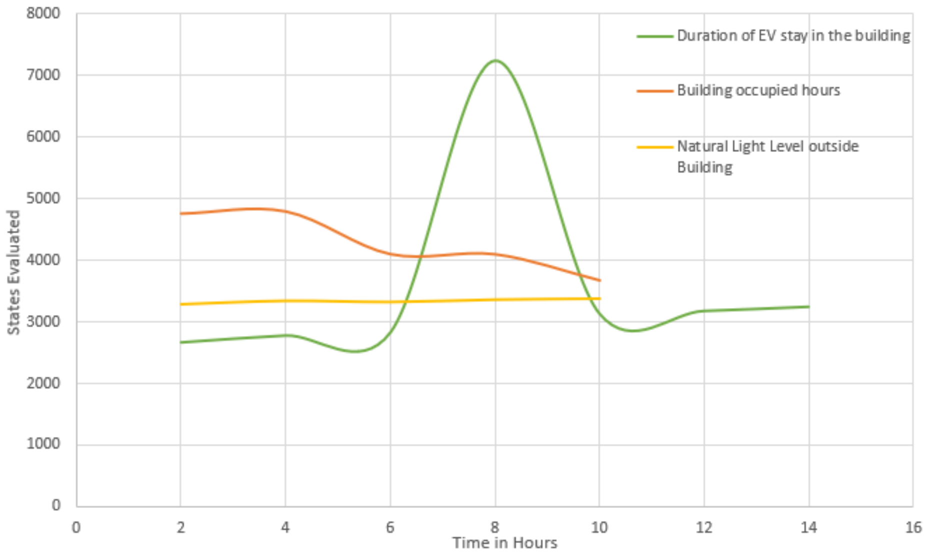

Figure 6.5: States Evaluated by simulating variables

EV Plugin Time and EV Plug Out Time

Figure 6.5 displays the outcomes for the "Duration of EV stays in building"parameter. This parameter signifies the duration for which an EV remains connected to the smart charger, potentially offering its battery capacity for building energy support.

The number of states evaluated by the planner exhibits notable fluctuations as the duration of EV stay varies. When the EV stays for shorter duration, such as 2, 4, or 6 hours, the number of states evaluated remains relatively moderate, with values ranging from 2671 to 2829. However, when the EV extends its stay to 8 hours, the number of states evaluated significantly increases to 7246. This substantial increase in states evaluated can be attributed to the extended time period, allowing for more complex planning scenarios.

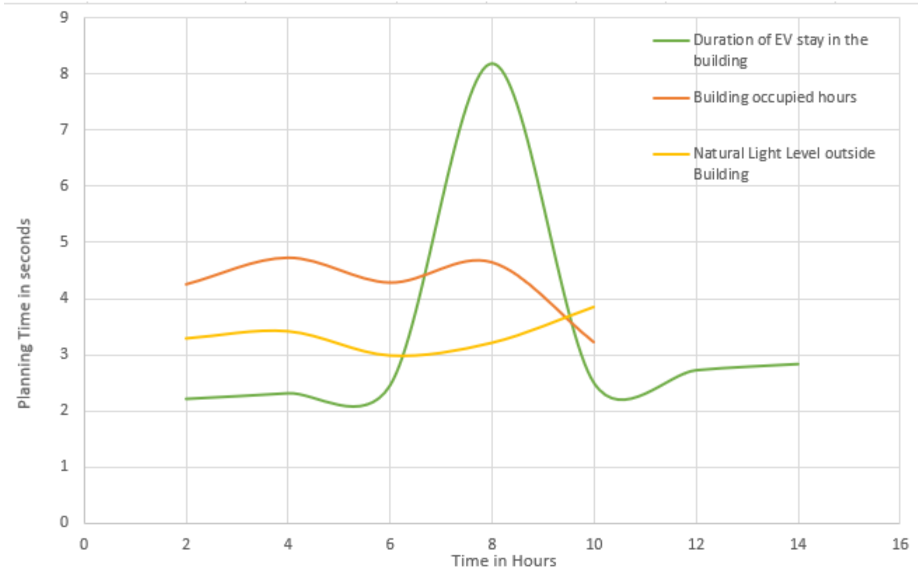

Figure 6.6: Planning Time taken by simulating variables

The time required for planning varies with the duration of EV stay (Figure 6.6). Shorter duration, such as 2, 4, and 6 hours, result in relatively quick planning times, with an average time of approximately 2.33 seconds. However, when the EV stays for 8 hours, the planning time substantially increases to 8.19 seconds. Longer duration of 10, 12, and 14 hours exhibit moderate planning times, ranging from 2.5 to 2.84 seconds.

The duration of EV stay has a noticeable impact on the number of states evaluated and the computational time required for planning. Longer duration lead to a significant increase in states evaluated and planning time, while shorter duration are associated with more efficient planning processes. These findings highlight the importance of optimizing the duration of EV stay in smart building scenarios to balance planning complexity and computational efficiency.

Building Occupancy

Figure 6.5 presents the outcomes for the Öccupied Hours "parameter. This parameter represents the number of hours during which the building is occupied, affecting the demand for energy and the planning process.

The number of states evaluated by the planner varies with different levels of occupied hours. As the building's occupancy duration increases from 2 to 10 hours, the number of states evaluated exhibits fluctuations. Occupied hours of 2 and 4 hours result in the highest number of states evaluated, with values of 4746 and 4781, respectively. As the occupancy duration increases to 6 and 8 hours, the number of states evaluated slightly decreases to 4090 and 4088, respectively. Finally, when the building is occupied for 10 hours, the number of states evaluated decreases further to 3665. This trend suggests that the duration of building occupancy has an impact on the complexity of planning, with shorter occupancy periods resulting in more states to evaluate.

In Figure 6.6, the planning time required for different occupied hours shows variations as well. When the building is occupied for 2 hours, the planning time is 4.25 seconds, while 4 hours of occupancy result in a planning time of 4.72 seconds. Occupancy duration of 6 and 8 hours lead to planning times of 4.28 and 4.64 seconds, respectively. However, when the building is occupied for 10 hours, the planning time decreases to 3.23 seconds. This indicates that shorter occupancy duration are associated with longer planning times, with 4 hours of occupancy having the longest planning time. Longer occupancy duration result in shorter planning times, with 10 hours of occupancy being the most efficient in terms of planning time.

The duration of building occupancy significantly influences the number of states evaluated and the planning time required. Shorter occupancy periods result in more states to evaluate and longer planning times, while longer occupancy periods lead to fewer states evaluated and more efficient planning processes. These findings emphasize the importance of accurately modeling building occupancy patterns in smart building planning to optimize computational efficiency and energy utilization.

Natural Light Outside the Building

In this section, we delve into the impact of varying duration of high natural light availability outside the building on the performance of the POPF-TIF planner. The duration of high natural light plays a crucial role in influencing the building's reliance on artificial lighting and, consequently, its energy demand.

Examining the number of states evaluated by the planner reveals interesting insights in Figure 6.5. As the duration of high natural light hours increases from 2 to 10 hours, there is a modest fluctuation in the number of states evaluated. For instance, with only 2 hours of high natural light, the planner evaluates 3296 states. This number slightly rises to 3341 when there are 4 hours of high natural light. However, as the duration of high natural light hours extends to 6, 8, and 10 hours, the number of states evaluated remains relatively stable at 3326, 3357, and 3370, respectively. This indicates that the duration of high natural light has a marginal impact on planning complexity.

Turning our attention to planning time, we observe variations in Figure 6.6 associated with different duration of high natural light. When there are 2 hours of high natural light, the planning time amounts to 3.29 seconds. With 4 hours of high natural light, the planning time slightly increases to 3.42 seconds. Surprisingly, as the duration of high natural light hours reaches 6, the planning time decreases to 2.98 seconds. However, with 8 hours of high natural light, the planning time experiences a minor upturn to 3.21 seconds. Finally, when there are 10 hours of high natural light, the planning time further extends to 3.86 seconds. These fluctuations in planning time suggest that the impact of high natural light duration on planning efficiency is not linear.

The duration of high natural light hours exhibits a limited influence on the number of states evaluated and planning time. Changes in the duration of high natural light hours result in minor variations in the number of states evaluated and planning time, emphasizing that this parameter has a relatively consistent effect on planning complexity and computational efficiency. While the duration of high natural light is a significant factor for optimizing energy utilization in smart buildings, its impact on planning efficiency is not highly pronounced.

Building Temperature (in Degrees Celsius)

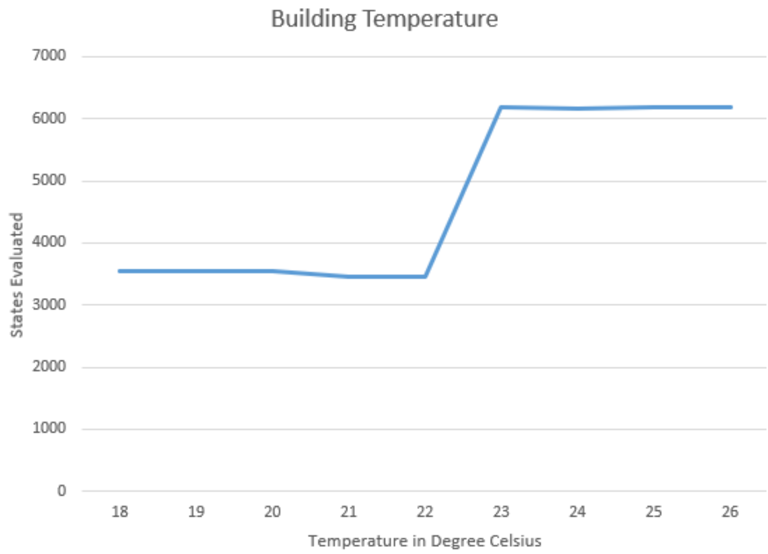

Figure 6.7: States Evaluated by simulating Building Temperature

In this section, we explore the impact of varying indoor temperatures, represented in degrees Celsius, on the performance of the POPF-TIF planner. The building's temperature is a crucial factor in maintaining a comfortable indoor environment while optimizing energy usage. We consider a range from 18°C to 26°C to account for different climate conditions and heating or cooling requirements.

Analyzing the number of states evaluated by the planner in Figure 6.7, we observe interesting trends related to temperature settings. When the building temperature is set to 18°C, the planner evaluates 3554 states. Slight variations are observed as the temperature increases incrementally to 19°C and 20°C, with 3546 states evaluated in both cases. However, as the temperature moves beyond 20°C and reaches 21°C and 22°C, the number of states evaluated remains at 3465, suggesting that minor temperature adjustments do not significantly affect planning complexity.

Remarkably, the number of states evaluated experiences a substantial increase as the building temperature enters the range of 23°C to 26°C. When the temperature is set to 23°C, 6177 states are evaluated, and this number remains consistent for temperatures of 24°C, 25°C, and 26°C. This significant change indicates that planning complexity is notably influenced by indoor temperatures within this range, suggesting a critical threshold for the building's temperature settings.

Turning to planning time in Figure 6.8, we find variations in the time required to compute plans based on temperature settings. For temperatures ranging from 18°C to 22°C, planning times are relatively stable, with fluctuations in the second range. However, as the temperature reaches 23°C, the planning time increases to 5.56 seconds, a pattern that persists for temperatures of 24°C, 25°C, and 26°C. This substantial increase in planning time aligns with the surge in states evaluated within the critical temperature range of 23°C to 26°C.

In summary, building temperature has a substantial impact on the performance of the POPF-TIF planner. Temperature settings within the range of 23°C to 26°C significantly increase planning complexity, as evidenced by the substantial rise in states evaluated and planning time. These

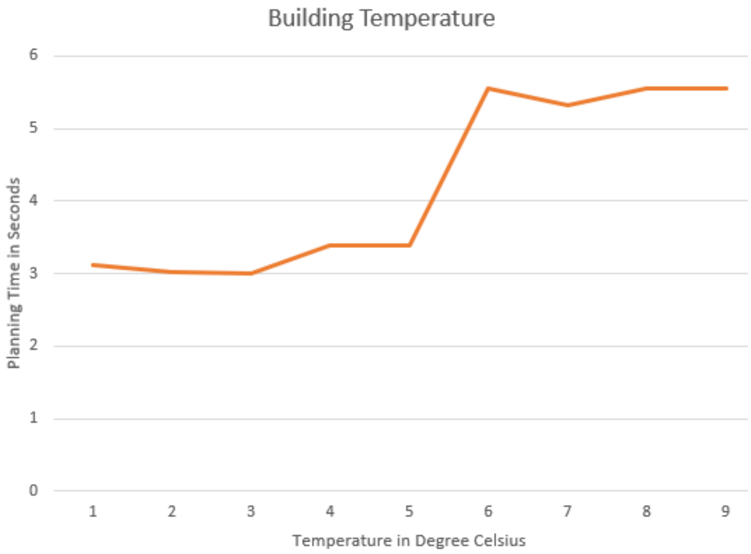

Figure 6.8: Planning Time by simulating Building Temperature

findings underscore the importance of considering indoor climate control in smart building planning and optimization, as extreme temperature settings can substantially affect computational efficiency and energy usage.

Working Day

In this analysis, we investigate the impact of different working day scenarios on the performance of the POPF-TIF planner. The building's operational hours and occupancy patterns during these working day scenarios play a crucial role in energy optimization and planning.

When the building operates as a full-day working environment, with occupants present for an entire day, the planner evaluates 4088 states. This scenario, which represents the highest level of building activity, requires 4.64 seconds for planning computation. The increased number of states evaluated and planning time in this setting reflects the complexity of managing energy and environmental conditions in a fully occupied building throughout the day.

In contrast, when the building operates as a half-day working environment, with occupants present for a shorter duration, the planner evaluates fewer states—specifically, 2896 states. This reduced occupancy pattern results in a shorter planning time of 2.40 seconds. The decrease in states evaluated and planning time aligns with the lower energy demands and environmental adjustments needed during a half-day working scenario.

On holidays, when the building experiences minimal or no occupancy, planning becomes significantly less complex. The planner evaluates only 185 states, reflecting the reduced need for energy optimization and environmental control during holidays. Planning for this scenario is highly efficient, taking only 0.16 seconds.

The working day scenario has a substantial impact on the performance of the POPF-TIF planner. Full-day working environments with continuous occupancy result in the highest complexity in terms of states evaluated and planning time. In contrast, half-day working scenarios lead to reduced planning complexity, while holidays require minimal planning efforts due to limited occupancy. These findings emphasize the importance of considering working day patterns when optimizing energy usage and indoor environments in smart buildings, as different scenarios have varying planning requirements and computational demands.

6.3 Summary

In this comprehensive analysis of integrating EVs with smart buildings using temporal planning, we explored various parameters and their impact on the performance of the POPF-TIF planner. The experimental design encompassed a range of variables, including EV state of charge, duration of EV stays, minimum charge limit SOC, building occupancy, natural light availability, building temperature, and working day simulations.

EV SOC, EV minimum charge limit SOC, and the duration of EV stay have the most significant impact on planning computation. These variables exhibit notable fluctuations in states evaluated and planning time. In contrast, building occupancy during holidays and natural light availability have less influence on planning, with fewer fluctuations in states evaluated and planning time. These findings provide valuable insights for optimizing energy consumption and indoor environments in smart buildings, highlighting the need for careful consideration of these variables in the planning process.

7 Conclusion

7.1 Conclusion

In conclusion, this thesis aimed to demonstrate the successful integration of EVs with smart buildings using temporal planning. The primary objective was to showcase the potential benefits for both building operations and EV owners beyond conventional transportation use. We achieved this by employing temporal planning, a sub field of AI planning, and leveraging energy market data, EV information, and building environment data.

Our temporal planning model generated full-day plans to optimize energy consumption in a commercial building while efficiently charging EVs at minimal cost. This approach not only met occupants' needs but also contributed to grid stability.

The evaluation of our approach highlighted the significant influence of various parameters on the performance of the POPF planner. Nonetheless, it demonstrated the feasibility of integrating EVs with smart buildings through temporal planning.

our proposed temporal planning approach holds the potential to substantially reduce energy consumption and operational costs in commercial buildings, promoting sustainability in the built environment and benefiting EV owners. This work paves the way for further exploration and implementation of intelligent energy management systems in the future

7.2 Future work

Future work in our project domain can be explored by concentrate on augmenting the sustainability and autonomy of smart buildings through the integration of renewable energy sources into the existing model. This involves exploring the synergy between V2B technology and intermittent renewable like photovoltaic (PV) and wind power to mitigate energy losses during battery cycling. Additionally, investigating the incorporation of Combined Heat and Power (CHP) or Combined Cooling, Heat, and Power (CCHP) systems to boost energy efficiency and reduce emissions is crucial.

Furthermore, the exploration of alternative planners for temporal planning, such as LPG-TD and UPMurphi, offers the potential to alleviate some of the design compromises made in the domain and problem files to accommodate the limitations of the existing planner, POPF-TIF. If these alternative planners demonstrate superior performance in handling complex temporal constraints and large action spaces, it may eliminate the need for such compromises and lead to more streamlined and efficient planning processes for integrating EVs with smart buildings. This research direction can ultimately contribute to the development of comprehensive planning solutions that fully exploit the potential of EVs in smart building environments while maintaining planning optimality and scalability.

To advance this research further, a vital avenue for future work lies in the validation of the generated plans within a real-world commercial building context equipped with active EV chargers. The practical execution of these plans under genuine operational conditions would yield invaluable insights into the tangible implications and performance of the temporal planning approach. By closely monitoring and evaluating the execution process, any challenges or issues that may manifest in a real-world setting can be identified, enabling necessary refinements to enhance the approach's efficacy. This practical application not only serves to validate plan accuracy but also provides a deeper understanding of the approach's feasibility and scalability, facilitating its successful integration into smart building systems

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A Appendix

A.1 Domain Model

```
(define (domain schedule)

(:requirements :strips :fluents :durative-actions :timed-initial-literals :duration-inequalities)
(:predicates
    (working-day)
    (not_working-day)
    (Occupied)
    (NotOccupied)
    ;;;___________________24 Hours of the day_____________________;;;
    (dayEnd)
    (dayStart)
    (Day_Ahead_Plan)
    (enable)
    ;;;____________________________Semaphores____________________________;;;
    (speaking_Battery)
    (speaking_NotWorkingDay)
    (speaking_HVAC)
    (speaking_Lights)
    (speaking_Uncontrollable_Loads)
    ;;;___________________Uncontrollable Loads_________________________;;;
    (Uncontrollable_LightLoads_ON)
    (Uncontrollable_LightLoads_OFF)

    (Uncontrollable_HeavyLoads_ON)
    (Uncontrollable_HeavyLoads_OFF)
    ;;;___________________Controllable Independent Loads_________________________;;;

    (Controllable_Heavy_IndependentLoad_Dishwasher_ON)
    (Controllable_Heavy_IndependentLoad_Dishwasher_OFF)

    (controllable_light_Independentload_Situatedlights_ON)
    (controllable_light_Independentload_Situatedlights_OFF)

    ;;;___________________EV_________________________;;;
     (EV_Time_In)   ;; EV is plugged in time
     (Speaking_EV)
```

```
)
(:functions
    (time-lapse)
    (Energy_Tariff)
;;;____________________EV Numerics__________________;;;
    (EV_SOC_Percentage)
    (EV_Min_Charge_at_Time_Out)
    (EV_Priority)  ;; 0 = high priority, 1 = low priority

    (EV_discharge_rate_highprice)
    (EV_frequency)
    (EV_Discharge_rate_nominalprice)
    (EV_charge_rate)
    (ev_hours)
;;;___________________Battery Numerics__________________;;;
    (Battery_SOC_Percentage)
    (batterybank)
    (Battery_Recharge_Rate)
    (Battery_Discharge_Rate_HighPrice)
    (Battery_Discharge_Rate_NominalPrice)
    (EnergyBackupCapacity)

;;;____________________Heavy Controllable Dependent Loads - HVAC Numerics__________________;;;

    (HVAC_Intensity)
    (buildinghvac)
    (comfort-max-limit)
    (comfort-min-limt)
    (current-temp)
    (HeavyControllableDependentLoad)
    (TempDecreaseRate)
    (heavylightloads)
    (TempIncreaseRate_HighPrice_Occupied_NotTempRange)
    (TempIncreaseRate_HighPrice_NotOccupied)

    (TempIncreaseRate_NominalPrice_Occupied_TempRange)
    (TempIncreaseRate_NominalPrice_Occupied_NotTempRange)
    (TempIncreaseRate_NominalPrice_NotOccupied)
    (TempIncreaseRate_LowPrice)


;;;____________________Light Controllable Dependent Loads - Ordinary Lights Numerics__________________;;;

    (NaturalLightLevel)
    (ordinarylights)
    (Reduce_Light_Intensity_Percentage)
    (ControllableDependentLightLoad)
```

```
    (AllUncontrollableLoads)
    (hours)
)
;;;;:::::::::::::::::::::::::::::::;;;;
;;                                  ;;
;;           EV Data                ;;
;;                                  ;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

;;;___________________EV at High Energy Prices_________________________;;;

(:durative-action EV_Discharge_HighPrice_aboveMinCharge_High_Priority
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (=(Energy_Tariff) 0))    ;; High Price
        (over all (=(EV_Priority) 0))   ;; high priority
    (at start (Speaking_EV))
    (at start (EV_Time_In))
    (at start (enable))
    (over all (>=(EV_SOC_Percentage)20))
    (over all (<=(EV_SOC_Percentage)100))
    (over all (>(EV_SOC_Percentage)(EV_Min_Charge_at_Time_Out)))
    )
    :effect (and
            (at end (decrease (EV_SOC_Percentage)(EV_discharge_rate_highprice)))
    ;;battery discharging at higher rate till min threshold

            (at end (increase (EV_frequency)time-lapse))
            (at start (not(Speaking_EV)))
            (at end(Speaking_EV))
            )
)

(:durative-action EV_Discharge_HighPrice_aboveMinCharge_Low_Priotity
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
         (at start (EV_Time_In))
         (at start (enable))
        (over all (=(Energy_Tariff) 0))    ;; High Price
        (over all (=(EV_Priority) 1))   ;; Low priority
    (at start (Speaking_EV))
        (over all (>=(EV_SOC_Percentage)20))
    (over all (<=(EV_SOC_Percentage)100))
    )
    :effect (and
```

```
    (at end (decrease (EV_SOC_Percentage)(EV_discharge_rate_highprice)))
    ;;battery discharging at higher rate
    (at end (increase (EV_frequency)time-lapse))
    (at start (not(Speaking_EV)))
     (at end(Speaking_EV))
            )
)

(:durative-action EV_Charge_HighPrice_BelowMinCharge_High_Priority
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
         (at start (EV_Time_In))
         (at start (enable))
        (over all (=(Energy_Tariff) 0))    ;; High Price
        (over all (=(EV_Priority) 0))   ;; high priority
    (at start (Speaking_EV))
    (over all (>=(EV_SOC_Percentage)20))
    (over all (<=(EV_SOC_Percentage)100))
    (over all (<=(EV_SOC_Percentage)(EV_Min_Charge_at_Time_Out)))
    )
    :effect (and
            (at end (increase (EV_SOC_Percentage)(EV_charge_rate)))
            ;;battery charging at higher rate till min threshold
            (at end (increase (EV_frequency)time-lapse))
            (at start (not(Speaking_EV)))
            (at end(Speaking_EV))
            )
)

(:durative-action EV_Discharge_HighPrice_BelowMinCharge_Low_Priority
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
         (at start (EV_Time_In))
         (at start (enable))
        (over all (=(Energy_Tariff) 0))    ;; High Price
        (over all (=(EV_Priority) 1))   ;; Low priority
    (at start (Speaking_EV))
    (at start (<=(EV_SOC_Percentage)(EV_Min_Charge_at_Time_Out)))
        (over all (>=(EV_SOC_Percentage)10))
    )
    :effect (and
        (at end (decrease (EV_SOC_Percentage)(EV_discharge_rate_highprice)))
        ;;battery discharging at higher rate
        (at end (increase (EV_frequency)time-lapse))
        (at start (not(Speaking_EV)))
```

```
        (at end(Speaking_EV))
            )
)

;;;___________________EV at Nominal Energy Prices_________________________;;;

(:durative-action EV_Discharge_NominalPrice_aboveMinCharge_High_Priority
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (=(Energy_Tariff) 1))    ;; Nominal Price
        (over all (=(EV_Priority) 0))   ;; high priority
    (at start (Speaking_EV))
    (at start (enable))
    (at start (EV_Time_In))
    (over all (>=(EV_SOC_Percentage)20))
    (over all (<=(EV_SOC_Percentage)100))
    (over all (>(EV_SOC_Percentage)(EV_Min_Charge_at_Time_Out)))
    )
    :effect (and
        (at end (decrease (EV_SOC_Percentage)(EV_Discharge_rate_nominalprice)))
        ;;battery discharging at nominal rate till min threshold

        (at end (increase (EV_frequency)time-lapse))
        (at start (not(Speaking_EV)))
        (at end(Speaking_EV))
            )
)

(:durative-action EV_Idle_NominalPrice_Low_Priority
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (at start (EV_Time_In))
        (at start (enable))
        (over all (=(Energy_Tariff) 1))    ;; Nominal Price
        (over all (=(EV_Priority) 1))   ;; Low priority
    (at start (Speaking_EV))
    (over all (<=(EV_SOC_Percentage)100))
    )
    :effect (and
            (at end (increase (EV_frequency)time-lapse))   ;;SOC is Idle
            (at start (not(Speaking_EV)))
            (at end(Speaking_EV))
            )
)
```

```
(:durative-action EV_Charge_NominalPrice_BelowMinCharge_No_Priority
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (at start (EV_Time_In))
        (at start (enable))
        (over all (=(Energy_Tariff) 1))    ;; Nominal Price
    (at start (Speaking_EV))
    (over all (>=(EV_SOC_Percentage)20))
    (over all (<=(EV_SOC_Percentage)100))
    (at start (<=(EV_SOC_Percentage)(EV_Min_Charge_at_Time_Out)))
    )
    :effect (and
            (at end (increase (EV_SOC_Percentage)(EV_charge_rate)))
            ;;battery charging at nominal rate
            (at end (increase (EV_frequency)time-lapse))
            (at start (not(Speaking_EV)))
            (at end(Speaking_EV))
            )
)

;;;___________________EV at Low Energy Prices_________________________;;;

(:durative-action EV_Charge_LowPrice
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (=(Energy_Tariff) 2))    ;; Low Price
    (at start (Speaking_EV))
    (at start (enable))
    (at start (EV_Time_In))
    (over all (<=(EV_SOC_Percentage)90))
    )
    :effect (and
            (at end (increase (EV_SOC_Percentage)(EV_charge_rate)))
            ;;battery charging
            (at end (increase (EV_frequency)time-lapse))
            (at start (not(Speaking_EV)))
            (at end(Speaking_EV))
            )
)

(:durative-action EV_SOC_Full
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
    (at start (Speaking_EV))
```

```
    (over all (=(Energy_Tariff) 2))   ;; Low Price
    (at start (enable))
    (at start (EV_Time_In))
    (over all (>=(EV_SOC_Percentage)90))
    )
    :effect (and
            (at end (increase (EV_frequency)time-lapse))
            (at start (not(Speaking_EV)))
            (at end(Speaking_EV))
            )
)

;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
 LIGHT CONTROLLABLE DEPENDENT LOAD EXAMPLE: Ordianry Lights
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;



;;;___________________Ordinary Lights at High Energy Prices_________________________;;;

(:durative-action Ordinary_Lights_Dim_HighPrice_Occupied_HighNaturalLight
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))  ;; working day
        (over all (=(Energy_Tariff) 0)) ;; High Price
        (over all (=(NaturalLightLevel) 0)) ;; High Natural Light
        (at start  (Occupied))
    (at start (speaking_Lights))
    (at start (enable))
    )
    :effect (and
            (at end (assign(Reduce_Light_Intensity_Percentage) 70))

            (at end (increase (ControllableDependentLightLoad)time-lapse))
            (at start (not(speaking_Lights)))
            (at end(speaking_Lights))
            )
)
(:durative-action Ordinary_Lights_Brighten_HighPrice_Occupied_LowNaturalLight
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))  ;; working day
        (over all (=(Energy_Tariff) 0)) ;; High Price
        (over all (=(NaturalLightLevel) 1)) ;; Low Natural Light
        (at start   (Occupied))
```

```
    (at start (speaking_Lights))
    (at start (enable))
    )
    :effect (and
            (at end (assign(Reduce_Light_Intensity_Percentage) 15))

            (at end (increase (ControllableDependentLightLoad)time-lapse))
            (at start (not(speaking_Lights)))
            (at end(speaking_Lights))
            )
)
(:durative-action Ordinary_Lights_OFF_HighPrice_NotOccupied_HighNaturalLight
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))
        (over all (=(Energy_Tariff) 0)) ;; High Price
        (over all (=(NaturalLightLevel) 0)) ;; High Natural Light
        (at start   (NotOccupied))
    (at start (speaking_Lights))
    (at start (enable))
    )
    :effect (and
            (at end (assign(Reduce_Light_Intensity_Percentage) 100))

            (at end (increase (ControllableDependentLightLoad)time-lapse))
            (at start (not(speaking_Lights)))
            (at end(speaking_Lights))
            )
)
(:durative-action Ordinary_Lights_Dim_HighPrice_NotOccupied_LowNaturalLight
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))
        (over all (=(Energy_Tariff) 0)) ;; High Price
        (over all (=(NaturalLightLevel) 1)) ;; Low Natural Light
        (at start   (NotOccupied))
    (at start (speaking_Lights))
    (at start (enable))
    )
    :effect (and
            (at end (assign(Reduce_Light_Intensity_Percentage) 90))

            (at end (increase (ControllableDependentLightLoad)time-lapse))
            (at start (not(speaking_Lights)))
            (at end(speaking_Lights))
```

```
            )
)

;;;___________________Lights at Nominal Energy Prices_________________________;;;

(:durative-action Ordinary_Lights_Dim_NominalPrice_Occupied_HighNaturalLight
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))
        (over all (=(Energy_Tariff) 1)) ;; Nominal Price
        (over all (=(NaturalLightLevel) 0)) ;; High Natural Light
        (at start  (Occupied))
    (at start (speaking_Lights))
    (at start (enable))
    )
    :effect (and
            (at end (assign(Reduce_Light_Intensity_Percentage) 60))
            ;; reduce existing lights load by 60%

            (at end (increase (ControllableDependentLightLoad)time-lapse))
            (at start (not(speaking_Lights)))
            (at end(speaking_Lights))
            )
)
(:durative-action Ordinary_Lights_Brighten_NominalPrice_Occupied_LowNaturalLight
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))
        (over all (=(Energy_Tariff) 1)) ;; Nominal Price
        (over all (=(NaturalLightLevel) 1)) ;; Low Natural Light
        (at start  (Occupied))
    (at start (speaking_Lights))
    (at start (enable))
    )
    :effect (and
            (at end (assign(Reduce_Light_Intensity_Percentage) 15))
            ;; reduce existing lights load by 15%

            (at end (increase (ControllableDependentLightLoad)time-lapse))
            (at start (not(speaking_Lights)))
            (at end(speaking_Lights))
            )
)

(:durative-action Ordinary_Lights_OFF_NominalPrice_NotOccupied_HighNaturalLight
```

```
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))
        (over all (=(Energy_Tariff) 1)) ;; Nominal Price
        (over all (=(NaturalLightLevel) 0)) ;; High Natural Light
        (at start   (NotOccupied))
    (at start (speaking_Lights))
    (at start (enable))
    )
    :effect (and
            (at end (assign(Reduce_Light_Intensity_Percentage) 100))
            ;; Lights are off
            (at end (increase (ControllableDependentLightLoad)time-lapse))
            (at start (not(speaking_Lights)))
            (at end(speaking_Lights))
            )
)
(:durative-action Ordinary_Lights_Dim_NominalPrice_NotOccupied_LowNaturalLight
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))
        (over all (=(Energy_Tariff) 1)) ;; Nominal Price
        (over all (=(NaturalLightLevel) 1)) ;; Low Natural Light
        (at start   (NotOccupied))
    (at start (speaking_Lights))
    (at start (enable))
    )
    :effect (and
            (at end (assign(Reduce_Light_Intensity_Percentage) 90))
            ;; reduce existing lights load by 90%
            (at end (increase (ControllableDependentLightLoad)time-lapse))
            (at start (not(speaking_Lights)))
            (at end(speaking_Lights))
            )
)

;;;___________________Lights at Low Energy Prices_________________________;;;

(:durative-action Ordinary_Lights_LowPrice_Occupied_HighNaturalLight
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))
        (over all (=(Energy_Tariff) 2)) ;; Low Price
        (over all (=(NaturalLightLevel) 0)) ;; High Natural Light
```

```
        (at start   (Occupied))
    (at start (speaking_Lights))
    (at start (enable))
    )
    :effect (and
            (at end (assign(Reduce_Light_Intensity_Percentage) 50))
            ;; reduce existing lights load by 50%
            (at end (increase (ControllableDependentLightLoad)time-lapse))
            (at start (not(speaking_Lights)))
            (at end(speaking_Lights))
            )
)
(:durative-action Ordinary_Lights_Brighten_LowPrice_Occupied_LowNaturalLight
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))
        (over all (=(Energy_Tariff) 2)) ;; Low Price
        (over all (=(NaturalLightLevel) 1)) ;; Low Natural Light
        (at start   (Occupied))
    (at start (speaking_Lights))
    (at start (enable))
    )
    :effect (and
            (at end (assign(Reduce_Light_Intensity_Percentage) 0))
        ;; turn ON lights at maximum demand level
            (at end (increase (ControllableDependentLightLoad)time-lapse))
            (at start (not(speaking_Lights)))
            (at end(speaking_Lights))
            )
)

(:durative-action Ordinary_Lights_OFF_LowPrice_NotOccupied_HighNaturalLight
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))
        (over all (=(Energy_Tariff) 2)) ;; Low Price
        (over all (=(NaturalLightLevel) 0)) ;; High Natural Light
        (at start  (NotOccupied))
    (at start (speaking_Lights))
    (at start (enable))
    )
    :effect (and
            (at end (assign(Reduce_Light_Intensity_Percentage) 100))
            ;; turn off lights
            (at end (increase (ControllableDependentLightLoad)time-lapse))
```

```
            (at start (not(speaking_Lights)))
            (at end(speaking_Lights))
            )
)
(:durative-action Ordinary_Lights_Dim_LowPrice_NotOccupied_LowNaturalLight
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))
        (over all (=(Energy_Tariff) 2)) ;; Low Price
        (over all (=(NaturalLightLevel) 1)) ;; Low Natural Light
        (at start  (NotOccupied))
    (at start (speaking_Lights))
    (at start (enable))
    )
    :effect (and
            (at end (assign(Reduce_Light_Intensity_Percentage) 40))
            ;; rreduce existing lights load by 40%
            (at end (increase (ControllableDependentLightLoad)time-lapse))
            (at start (not(speaking_Lights)))
            (at end(speaking_Lights))
            )
)

;;;;::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
;;                 LIGHT UNCONTROLLABLE LOAD                      ;;
;;                 HEAVY UNCONTROLLABLE LOAD                      ;;
;;  LIGHT CONTROLLABLE INNDEPENDENT LOAD EXAMPLE Situated Lights  ;;
;;  HEAVY CONTROLLABLE INNDEPENDENT LOAD EXAMPLE Dish Washer      ;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;



;;;___________________High Energy Prices_________________________;;;

(:durative-action Uncontrollable_Loads_Controllable_Independent_Loads_HighPrice
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))
        (over all (=(Energy_Tariff) 0)) ;; High Price
    (at start (speaking_Uncontrollable_Loads))
    (at start (enable))
    )
    :effect (and
        (at start (Uncontrollable_LightLoads_ON))
            ;;Uncontrollable_LightLoads (Sckets, Tv): ON Battery
```

```
        (at end (not(Uncontrollable_LightLoads_OFF)))

        (at start (Uncontrollable_HeavyLoads_ON))
            ;;Uncontrollable_HeavyLoads (Oven, Stove): ON Battery
        (at end (not(Uncontrollable_HeavyLoads_OFF)))

        (at start (Controllable_Heavy_IndependentLoad_Dishwasher_OFF))
            ;; Dish washer: OFF
        (at start (not(Controllable_Heavy_IndependentLoad_Dishwasher_ON)))

        (at start (Controllable_Light_IndependentLoad_SituatedLights_OFF))
            ;; Situated Lights: OFF
        (at start (not(Controllable_Light_IndependentLoad_SituatedLights_ON)))
            (at end (increase (AllUncontrollableLoads)time-lapse))
            (at start (not(speaking_Uncontrollable_Loads)))
            (at end(speaking_Uncontrollable_Loads))
            )
)

;;;___________________Nominal Energy Prices_________________________;;;

(:durative-action Uncontrollable_Loads_Controllable_Independent_Loads_NominalPrice
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))
        (over all (=(Energy_Tariff) 1)) ;; Nominal Price
    (at start (speaking_Uncontrollable_Loads))
    (at start (enable))
    )
    :effect (and
            (at start (Uncontrollable_LightLoads_ON))
            ;;Uncontrollable_LightLoads (Sckets, Tv): ON
            (at end (not(Uncontrollable_LightLoads_OFF)))
            (at start (Uncontrollable_HeavyLoads_ON))
            ;;Uncontrollable_HeavyLoads (Oven, Stove):
            ON Battery if >80% SOC
            (at end (not(Uncontrollable_HeavyLoads_OFF)))
            (at start (Controllable_Heavy_IndependentLoad_Dishwasher_ON))
            ;; Dish washer: ON
            (at start (not(Controllable_Heavy_IndependentLoad_Dishwasher_OFF)))
            (at start (Controllable_Light_IndependentLoad_SituatedLights_ON))
            ;; Situated Lights: ON
            (at start (not(Controllable_Light_IndependentLoad_SituatedLights_OFF)))

            (at end (increase (AllUncontrollableLoads)time-lapse))
            (at start (not(speaking_Uncontrollable_Loads)))
```

```
            (at end(speaking_Uncontrollable_Loads))
            )
)

;;;___________________Low Energy Prices_________________________;;;

(:durative-action Uncontrollable_Loads_Controllable_Independent_Loads_LowPrice
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))
        (over all (=(Energy_Tariff) 2)) ;; Low Price
    (at start (speaking_Uncontrollable_Loads))
    (at start (enable))
    )
    :effect (and
        (at start (Uncontrollable_LightLoads_ON))   ;;Uncontrollable_LightLoads (Sckets, Tv): ON
            (at end (not(Uncontrollable_LightLoads_OFF)))

        (at start (Uncontrollable_HeavyLoads_ON))      ;;Uncontrollable_HeavyLoads (Oven, Stove): ON
            (at end (not(Uncontrollable_HeavyLoads_OFF)))

         (at start (Controllable_Heavy_IndependentLoad_Dishwasher_ON))  ;; Dish washer: ON
            (at start (not(Controllable_Heavy_IndependentLoad_Dishwasher_OFF)))

        (at start (Controllable_Light_IndependentLoad_SituatedLights_ON))  ;; Situated Lights: ON
            (at start (not(Controllable_Light_IndependentLoad_SituatedLights_OFF)))


            (at end (increase (AllUncontrollableLoads)time-lapse))
            (at start (not(speaking_Uncontrollable_Loads)))
            (at end(speaking_Uncontrollable_Loads))
            )
)



;;;::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
HEAVY CONTROLLABLE DEPENDENT LOAD EXAMPLE: HVAC
NOTE: Assumption is that its Winter season.
Room should be warm enough to be in Comfortable Temp Range
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

;;___________________HVAC High Energy Prices_________________________;;;

(:durative-action HVAC_HighPrice_InTempRange
    :parameters ()
```

```
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))
        (over all (=(Energy_Tariff) 0)) ;; high price
        (at start (speaking_HVAC))
        (over all (>=(current-temp)(comfort-min-limt)));; In Temp Range
    (over all (<=(current-temp )(comfort-max-limit)))
    (at start (enable))
    )
    :effect (and
            (at end (assign(HVAC_Intensity) 0))
            (at end(decrease (current-temp)(TempDecreaseRate)))
            (at end (increase (HeavyControllableDependentLoad)time-lapse))
            (at start (not(speaking_HVAC)))
            (at end(speaking_HVAC))
            )
)

(:durative-action HVAC_HighPrice_Occupied_NotInTempRange
     :parameters ()
     :duration (= ?duration 2)
     :condition (and
                (over all (working-day))
                (over all (=(Energy_Tariff) 0)) ;; high price
                (at start (Occupied))
                (over all (<= (current-temp) (comfort-min-limt)));; not In Temp Range
          (over all (<=(current-temp)(comfort-max-limit)))
          (at start (speaking_HVAC))
          (at start (enable))
      )
     :effect (and
             (at end (assign(HVAC_Intensity) 80))
        (at end(increase (current-temp)(TempIncreaseRate_HighPrice_Occupied_NotTempRange)))

             (at end (increase (HeavyControllableDependentLoad)time-lapse))
              (at start (not(speaking_HVAC)))
            (at end(speaking_HVAC))
             )
)

(:durative-action HVAC_HighPrice_NotOccupied_NotInTempRange
     :parameters ()
     :duration (= ?duration 2)
     :condition (and
                (over all (working-day))
                (over all (=(Energy_Tariff) 0)) ;; high price
                (at start (NotOccupied))
```

```
                (over all (<= (current-temp) (comfort-min-limt)));; not In Temp Range
          (over all (<=(current-temp)(comfort-max-limit)))
          (at start (speaking_HVAC))
          (at start (enable))
         )
      :effect (and
            (at end (assign(HVAC_Intensity) 50))
            (at end(increase (current-temp)(TempIncreaseRate_HighPrice_NotOccupied)))

            (at end (increase (HeavyControllableDependentLoad)time-lapse))
             (at start (not(speaking_HVAC)))
            (at end(speaking_HVAC))
            )
)

;;;___________________HVAC Nominal Energy Prices_________________________;;;

(:durative-action HVAC_NominalPrice_InTempRange
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))
        (over all (=(Energy_Tariff) 1)) ;; Nominal price
        (over all (>=(current-temp)(comfort-min-limt)));; In Temp Range
    (over all (<=(current-temp )(comfort-max-limit)))
    (at start (speaking_HVAC))
    )
    :effect (and
            (at end (assign(HVAC_Intensity) 70))
        (at end(increase (current-temp)(TempIncreaseRate_NominalPrice_Occupied_TempRange)))
            (at end (increase (HeavyControllableDependentLoad)time-lapse))
            (at start (not(speaking_HVAC)))
            (at end(speaking_HVAC))
            (at start (enable))
            )
)

(:durative-action HVAC_NominalPrice_Occupied_NotInTempRange
     :parameters ()
     :duration (= ?duration 2)
     :condition (and
                (over all (working-day))
                (over all (=(Energy_Tariff) 1)) ;; Nominal price
                (at start (Occupied))
                (over all (<= (current-temp) (comfort-min-limt)));; not In Temp Range
              (over all (<=(current-temp)(comfort-max-limit)))
              (at start (speaking_HVAC))
```

```
              (at start (enable))
       )
      :effect (and
             (at end (assign(HVAC_Intensity) 90))
         (at end(increase (current-temp)(TempIncreaseRate_NominalPrice_Occupied_NotTempRange)))
             (at end (increase (HeavyControllableDependentLoad)time-lapse))
             (at start (not(speaking_HVAC)))
             (at end(speaking_HVAC))
              )
)

(:durative-action HVAC_NominalPrice_NotOccupied_NotInTempRange
      :parameters ()
      :duration (= ?duration 2)
      :condition (and
                (over all (working-day))
                (over all (=(Energy_Tariff) 1)) ;; Nominal price
                (at start (NotOccupied))
                (over all (<= (current-temp) (comfort-min-limt)));; not In Temp Range
              (over all (<=(current-temp)(comfort-max-limit)))
              (at start (speaking_HVAC))
              (at start (enable))
       )
      :effect (and
             (at end (assign(HVAC_Intensity) 70))
             (at end(increase (current-temp)(TempIncreaseRate_NominalPrice_NotOccupied)))
             (at end (increase (HeavyControllableDependentLoad)time-lapse))
             (at start (not(speaking_HVAC)))
             (at end(speaking_HVAC))
             )
)

;;;___________________HVAC Low Energy Prices_________________________;;;

(:durative-action HVAC_LowPrice_InTempRange
     :parameters ()
     :duration (= ?duration 2)
     :condition (and
         (over all (working-day))
         (over all (=(Energy_Tariff) 2)) ;; Low price
         (over all (>=(current-temp)(comfort-min-limt)));; In Temp Range
     (over all (<=(current-temp )(comfort-max-limit)))
     (at start (speaking_HVAC))
     (at start (enable))
     )
     :effect (and
             (at end (assign(HVAC_Intensity) 100))
```

```
            (at end(increase (current-temp)(TempIncreaseRate_LowPrice)))
            (at end (increase (HeavyControllableDependentLoad)time-lapse))
            (at start (not(speaking_HVAC)))
            (at end(speaking_HVAC))
            )
)

(:durative-action Day_Ahead_Plan_24h
:parameters()
:duration (<= ?duration(Hours))
:condition(and
   (at start(dayStart))
   (at end (dayEnd))
   (over all (>= (Battery_SOC_Percentage)0))
   (over all (<= (Battery_SOC_Percentage)100))
   (at end (and
        (=(ControllableDependentLightLoad)(OrdinaryLights))
       (=(AllUncontrollableLoads)(HeavyLightLoads)) ;; uncontrol + out of operating hours
        (=(EnergyBackupCapacity) (BatteryBank))
        (=(HeavyControllableDependentLoad) (BuildingHVAC))
        (=(EV_frequency)(EV_Hours))
   ))
)
:effect(and
(at start (enable))
(at end (not(enable)))
(at end(Day_Ahead_Plan)))
)

(:durative-action HVAC_LowPrice_Occupied_NotInTempRange
     :parameters ()
     :duration (= ?duration 2)
     :condition (and
                (over all (working-day))
                (over all (=(Energy_Tariff) 2)) ;; Low price
                (at start (Occupied))
                (over all (<= (current-temp) (comfort-min-limt)));; not In Temp Range
          (over all (<=(current-temp)(comfort-max-limit)))
          (at start (speaking_HVAC))
          (at start (enable))
      )
     :effect (and
             (at end (assign(HVAC_Intensity) 100))
             (at end(increase (current-temp) (TempIncreaseRate_LowPrice)))
             (at end (increase (HeavyControllableDependentLoad)time-lapse))
            (at start (not(speaking_HVAC)))
            (at end(speaking_HVAC))
```

```
             )
)

(:durative-action HVAC_LowPrice_NotOccupied_NotInTempRange
     :parameters ()
     :duration (= ?duration 2)
     :condition (and
                (over all (working-day))
                (over all (=(Energy_Tariff) 2)) ;; Low price
                (at start (NotOccupied))
                (over all (<= (current-temp) (comfort-min-limt)));; not In Temp Range
          (over all (<=(current-temp)(comfort-max-limit)))
          (at start (speaking_HVAC))
          (at start (enable))
      )
     :effect (and
            (at end (assign(HVAC_Intensity) 100))
            (at end(increase (current-temp) (TempIncreaseRate_LowPrice)))
            (at end (increase (HeavyControllableDependentLoad)time-lapse))
            (at start (not(speaking_HVAC)))
            (at end(speaking_HVAC))
            )
)

;;;;::::::::::::::::::::::::::::::::::::::::::::::
;; ELECTRICITY STORAGE SYSTEM EXAMPLE: Battery  ;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;


;;;__________________Battery Discharge at High Energy Prices________________________;;;

(:durative-action Battery_DisCharge_HighPrice
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (=(Energy_Tariff) 0))
    (at start (speaking_Battery))
    (at start (>(Battery_SOC_Percentage)0))
    (at start (enable))
    )
    :effect (and
          (at end (decrease (Battery_SOC_Percentage)(Battery_Discharge_Rate_HighPrice)))

            (at end (increase (EnergyBackupCapacity)time-lapse))
            (at start (not(speaking_Battery)))
            (at end(speaking_Battery))
            )
```

```
)

;;;__________________Battery Discharge at Nominal Energy Prices________________________;;;

(:durative-action Battery_DisCharge_NominalPrice
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (working-day))
        (over all (=(Energy_Tariff) 1))
    (at start (speaking_Battery))
    (at start (>(Battery_SOC_Percentage)0))
    (at start (enable))
    )
    :effect (and
        (at end (decrease (Battery_SOC_Percentage)(Battery_Discharge_Rate_NominalPrice)))

            (at end (increase (EnergyBackupCapacity)time-lapse))
            (at start (not(speaking_Battery)))
            (at end(speaking_Battery))
            )
)

;;;__________________Battery charge at Low Energy Prices________________________;;;


(:durative-action Battery_Charge_Low_Price
    :parameters ()
    :duration (= ?duration 2)
    :condition (and
        (over all (=(Energy_Tariff) 2)) ;; Low Price
    (at start (speaking_Battery))
    (at start (<(Battery_SOC_Percentage)100))
    (at start (enable))
    )
    :effect (and
            (at end (increase (Battery_SOC_Percentage)(Battery_Recharge_Rate)))

            (at end (increase (EnergyBackupCapacity)time-lapse))
            (at start (not(speaking_Battery)))
            (at end(speaking_Battery))
            )
)


;;;;::::::::::::::::::::::::::::::::::::::::::::::::::::
;; Out of Operating Hours / Weekends / Public Holidays ;;
```

```
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;


;;;_______________________Out of Operting Hours_________________________;;;

 (:durative-action Out_of_Operating_Hours_all_OFF_LightsReduced
    :parameters ()
    :duration (= ?duration 4)
    :condition (and
        (over all (Not_working-day))
    (at start (speaking_NotWorkingDay))
    (at start (enable))
    )
    :effect (and
             (at start (not(working-day))) ;; Not its Out of operation hours
             (at end (not(working-day)))

             (at end (assign(HVAC_Intensity)0))     ;;HVAC: OFF

         (at end (assign(Reduce_Light_Intensity_Percentage)40))  ;; Reduce Light Intensity

         (at start (Uncontrollable_LightLoads_OFF))   ;;Uncontrollable_LightLoads (Sckets, Tv): OFF
             (at end (not(Uncontrollable_LightLoads_ON)))

         (at start (Uncontrollable_HeavyLoads_OFF))     ;;Uncontrollable_HeavyLoads (Oven, Stove): OFF
             (at end (not(Uncontrollable_HeavyLoads_ON)))

         (at start (Controllable_Heavy_IndependentLoad_Dishwasher_OFF))  ;; Dish washer: OFF
             (at start (not(Controllable_Heavy_IndependentLoad_Dishwasher_ON)))

         (at start (Controllable_Light_IndependentLoad_SituatedLights_OFF))  ;; Situated Lights: OFF
             (at start (not(Controllable_Light_IndependentLoad_SituatedLights_ON)))

            (at start (not(speaking_NotWorkingDay)))
            (at end (increase (AllUncontrollableLoads)time-lapse))
            (at end(speaking_NotWorkingDay))
            )
)
)
```

A.2 Problem File Sample

```
;;;::::::::::::::::::::::::::::::::
;                                 ;
;         Problem file            ;
```

```
;      from 00:00 to 24:00       ;
;                                ;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

(define (problem scheduling1) (:domain schedule)
(:init

;;;_____________________Problem file run for 24Hr (1 day)_________________;;;


(dayStart)       ;; Problem file 1 started from 00:00 to 24:00 of the day
(at 0.1 (not(dayStart)))
(at 25 (dayEnd))
(= (Hours)24)
(= (time-lapse)1)

;;;____________Operating Hours Schedule______________________;;;

;; working hours from 08:00 to 14:00
(Not_working-day)
(not(working-day))
(at 8 (working-day))
(at 8 (not(Not_working-day)))
(at 12 (working-day))
(at 12 (not(Not_working-day)))
(at 14 (Not_working-day))
(at 14 (not(working-day)))
(at 16 (Not_working-day))
(at 16 (not(working-day)))
(at 20 (Not_working-day))
(at 20 (not(working-day)))
(at 22 (Not_working-day))
(at 22 (not(working-day)))

 ;;;_______________Energy Prices___________________;;;
;; 2 Low, 1 Nominal, 0 High ;;
(= (Energy_Tariff)2)
(at 8 (= (Energy_Tariff)0))
(at 12 (= (Energy_Tariff)1))
(at 14 (= (Energy_Tariff)1))
(at 16 (= (Energy_Tariff)2))
(at 20 (= (Energy_Tariff)2))
(at 22 (= (Energy_Tariff)2))

;;;_____________Occupancy Schedule_________________;;;
(not(Occupied))
(NotOccupied)
```

```
(at 8 (Occupied))
(at 10 (not(Occupied)))
(at 12 (Occupied))
(at 14 (Occupied))
(at 16 (Occupied))
(at 20 (not(Occupied)))
(at 22 (not(Occupied)))
(at 8 (not(NotOccupied)))
(at 10 (NotOccupied))
(at 12 (not(NotOccupied)))
(at 14 (not(NotOccupied)))
(at 16 (not(NotOccupied)))
(at 20 (NotOccupied))
(at 22 (NotOccupied))
;;;___________________Semaphore__________________________;;;

(speaking_Lights)
(speaking_Uncontrollable_Loads)
(speaking_Battery)
(speaking_NotWorkingDay)
(speaking_HVAC)
(=(AllUncontrollableLoads)0)

;;;________________HVAC ________________________;;;
(= (TempDecreaseRate)1)
(= (HeavyControllableDependentLoad)0)
(= (TempIncreaseRate_HighPrice_Occupied_NotTempRange)2)
(= (TempIncreaseRate_HighPrice_NotOccupied)1.5)
(= (TempIncreaseRate_NominalPrice_Occupied_TempRange)1.5)
(= (TempIncreaseRate_NominalPrice_Occupied_NotTempRange)3)
(= (TempIncreaseRate_NominalPrice_NotOccupied)1.5)
(= (TempIncreaseRate_LowPrice)3)
(= (comfort-max-limit)28)
(= (comfort-min-limt)23)
(= (current-temp)24)

;;;_______________Lights (Natural Light Schedule__________________;;;
(= (ControllableDependentLightLoad)0)
(= (NaturalLightLevel)1)  ;; 1 Low
(at 8 (= (NaturalLightLevel)0)) ;; 0 High
(at 12 (= (NaturalLightLevel)0)) ;; 0 High
 (at 14 (= (NaturalLightLevel)1)) ;; 0 High
 (at 16 (= (NaturalLightLevel)1)) ;; 0 High
 (at 20 (= (NaturalLightLevel)1)) ;; 1 Low
 (at 22 (= (NaturalLightLevel)1)) ;; 1 Low

;;;__________________________Battery variables___________________;;
```

```
(= (Battery_SOC_Percentage)40)
(= (Battery_Recharge_Rate)20)
(=(EnergyBackupCapacity)0)
(= (Battery_Discharge_Rate_NominalPrice)4)
(= (Battery_Discharge_Rate_HighPrice)7)
;;;____________________________EV__________________________;;;
(speaking_EV)
(= (EV_frequency)0)
(at 8 (EV_Time_In))
(at 12 (EV_Time_In))
(at 14 (EV_Time_In))
(at 16 (EV_Time_In))
(at 20 (not(EV_Time_In)))
(at 22 (not(EV_Time_In)))
;;;___________________________EV variables____________________;;;
(= (EV_discharge_rate_highprice)10)
(= (EV_Discharge_rate_nominalprice)5)
(= (EV_charge_rate)10)
(= (EV_SOC_Percentage)50)
(= (EV_Min_Charge_at_Time_Out)40)
;;;______________________EV Priority___________________;;;
;; 1 Low priority, 0 High priority ;;
(= (EV_Priority)1)
(at 8 (=(EV_Priority)1))
(at 12 (=(EV_Priority)1))
(at 14 (=(EV_Priority)0))
(at 16 (=(EV_Priority)0))
(at 20 (=(EV_Priority)0))
(at 22 (=(EV_Priority)0))
)
(:goal (and
 (Day_Ahead_Plan)
)
)
)
```

Declaration

I hereby declare that the work presented in this thesis is entirely my own and that I did not use any other sources and references than the listed ones. I have marked all direct or indirect statements from other sources contained therein as quotations. Neither this work nor significant parts of it were part of another examination procedure. I have not published this work in whole or in part before. The electronic copy is consistent with all submitted copies.

Stuttgart, 13.10.2023

place, date, signature