Institute of Architecture of Application Systems

University of Stuttgart
Universitätsstraße 38
D–70569 Stuttgart

Bachelorarbeit

AI Planning for improved Ventilation Management in Buildings

Claudio Stanullo

Course of Study:	Informatik
Examiner:	Prof. Dr. Marco Aiello
Supervisor:	Dr. Ilche Georgievski, Dipl.-Inf. Ralph Briegl
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Abstract

Office buildings in particular have high energy consumption followed by high operational costs and emissions. In addition, regulated air exchange is becoming increasingly necessary due to the COVID-19 pandemic. While current building management systems work with primitive rules and basic scheduling functions, Demand-Side Management (DSM) allows smart solutions by using Internet of Things (IoT) devices.

Artificial Intelligence (AI) planning can be used to plan the energy demand of buildings intelligently. It provides powerful techniques for the automated and dynamic selection and organization of actions that, when carried out, achieve a specific goal.

In this thesis a Demand-Side Management system with AI planning has been developed, which adjusts the temperature and CO2 values of an office room to a comfortable and healthy level. The company SPIRIT/21 equipped 12 office rooms with sensors and wants to test the developed system with real data gathered by them. The system, running with the OPTIC planner, uses the data to calculate an efficient solution, resulting in a comfortable indoor climate, regular air exchange, increased energy efficiency and in lower operating costs.

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Acronyms

AC air conditioner. 26

AI Artificial Intelligence. 15

ASHRAE American Society of Heating, Refrigerating and Air-Conditioning Engineers. 19

AWS Amazon Web Services. 31

CO2 carbon dioxide. 16

COVID-19 Coronavirus Disease 2019. 16

DSM Demand-Site Management. 15

ICAPS International Conference on Automated Planning and Scheduling. 26

IoT Internet of Things. 15

NOAA National Oceanic and Atmospheric Administration. 34

OPTIC Optimising Preferences and Time-Dependent Costs. 16

OWM OpenWeatherMap. 25

PDDL Planning Domain Description Language. 18

SARS-CoV-2 severe acute respiratory syndrome coronavirus type 2. 19

1 Introduction

1.1 Motivation and Objectives

In Asmiov's stories, attention is often drawn to conflict between robot rules, as is the case in the short story Runaround [Asi42]. In the story, there are the Three Laws of Robotics that every robot must obey.

1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2. A robot must obey the orders given it by human beings except where such orders would conflict with the first law.
3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Laws.

When the robot Speedy is ordered to get selenium from a more distant mine on Mercury, the robot does not return for a while, causing the owners of the robot to worry. The reason for this is a conflict between laws 2 and 3. The selenium source contains unforeseen danger to the robot. To neither break any of the rules, Speedy tries to get selenium without harming himself, which makes the robot run in circles around the selenium mine, where both compulsions are of equal strength.

The example shows that rule-based approaches, which provide more complex control functionalities, are characterized by several drawbacks. All possible situations in an environment must be predicted and covered by (many carefully designed) rules [GNN+17]. With the increasing complexity of the interrelationships, it is hardly possible to cover all situations. This can lead to contradictions or inefficient solutions.

Current building management systems are capable of controlling heating, ventilation, air conditioning, lighting and other aspects using specific strategies based on basic rules . For example, the temperature in an office is controlled by set thresholds. If the temperature exceeds a specified value, the air conditioning switches on automatically to cool the room down to a comfortable temperature. When the building management system becomes more complex, it is becoming increasingly difficult to set fixed rules.

Different to this, building management systems can be transformed to intelligent and adaptive Demand-Site Management (DSM) systems with the expanding use of Internet of Things (IoT) in buildings. Buildings can become smart with sensors and actuators to provide occupants with a more comfortable experience, reduced operational costs, and improved energy efficiency.

With increasing complexity, rule-based approaches can hardly be implemented due to lack of flexibility, lack of systematicity, a limited service order and the lack of reusability. [GNN+17] Artificial Intelligence (AI) Planning offers an approach to solve these complex problems.

Georgievski et al. note that AI planning is a mean of overcoming the challenges and disadvantages of the rules-based approach. AI Planning is an adaptable and flexible approach in which the actions are known and the domain model can be adapted to the environment. The real building environment can be described easily in a problem model. Possible actions, changing the environment, are specified in a domain model. The latter can potentially be used multiple times [GNN+17].

1.2 Objective of the thesis

The company SPIRIT/21[1] deployed 12 sensors in different business rooms which can collect various data. This data shall be used, on the one hand, to ensure a comfortable indoor temperature, and on the other hand, to keep or get the indoor carbon dioxide (CO2) value below a certain threshold to ensure a healthy level, which is particularly important during the Coronavirus Disease 2019 (COVID-19) pandemic. The solution, moreover, should minimize the energy costs as well as emissions.

The aim of this thesis is the development of a DSM system using AI planning. The sensors can be used to develop the system using real indoor data. The objective of this system is to find the most efficient way to manage temperature and CO2 values using ventilation, heating and cooling as possible actions. Finally, the Optimising Preferences and Time-Dependent Costs (OPTIC) planner will calculate a plan that describes the most efficient way to get towards the predefined goal.

1.3 Outline

The paper is structured in the following way:
Chapter 2 - Background Information: First, fundamental concepts like AI Planning and DSM will be explained. These concepts will be referred to in the thesis.
Chapter 3 - Design of the Solution: Represents the abstract design of the solution
Chapter 4 - Implementation: Provides implementation details and how the design is practically realized
Chapter 5 - Validation, Evaluation of the Solution: Validation and evaluation by analysis and interpretation of the work using visualization
Chapter 6 - Conclusion and Outlook: Summarizes the most important findings of the work and evaluates them in relation to the research question

[1] https://spirit21.com/

2 Background information

This chapter explains basic concepts that are relevant to this work.

2.1 Demand-Side Management

DSM is considered as a potential tool to optimize energy systems. The scope of DSM ranges from optimizing energy efficiency to controlling energy resources [PD11].

Modern office buildings can provide up-to-date context information with the equipment of sensors and actuators. The collected data can be used dynamically, together with personal preferences, to offer added value. The IoT network can be automatically coordinated with the extended ability [GNA13].

Building management systems are currently very limited and have simple, restrictive rules. Effective tools are needed to improve both user experience and energy efficiency [GNN+17].

Think of an office where air conditioning and heating is managed by a central managing system. The temperature will always be at a comfortable level, however, switching the devices on and off leads to high energy consumption. In addition, it is not taken into account when windows are open, which can lead to even higher energy consumption, as the devices now heat/ cool the outdoor temperature.

A strategy of DSM is to find these situations, where consumption can be reduced. An automated approach is the use of AI planning.

2.2 AI planning

The logical side of action is planning. The abstract counseling process selects actions and organizes them by predicting the consequences. Automated planning is an area of AI that tries to solve the deliberation process arithmetically [Gha04].

AI planning defines a planning problem using an initial state, a target state and a series of actions. The initial state describes the environment before the plan gets executed. The target state defines the desired state of the environment after the plan has been executed and is also called the planning domain. Actions in turn consist of parameters, condition and effects. The parameters can be filled with values to initiate specific actions. Preconditions contain predicates which must be fulfilled in order for an action to be carried out and, finally, effects contain predicates that simulate the action. Predicates can either have the value true or false and consist of names and parameters. The names describe the relationships between the parameters which, in combination with the set-in values, lead to a true or false value of the predicate. Carrying out an action transfers the state at the beginning of the action to a new state that is achieved through the effects. A plan is a series of actions. If it is applied to the initial state and it leads to the defined goal, it is called a solution to the planning problem [GA16].

In order to guarantee the implementation of a planning algorithm, a description of the problem to be solved including all possible states and state transitions must be supplied as input. In practice, this is usually not possible, as the description would be extremely extensive and would probably require more effort than solving the problem yourself. Therefore, the description of the problem should not have to explicitly specify all states and state transitions, but rather calculate them parenthetically [Gha04].

McDermott et al. [1998] defined a language to define inputs for planning problems called Planning Domain Description Language (PDDL). In PDDL you don't need to specify any intermediate environment state.

2.3 Planning Domain Description Language

PDDL is a language with the focus on actions. It is particularly inspired by the Stanford Research Institute Problem Solver (STRIPS) developed by [FN71]. The language formulates planning problems with the help of a simple and standardized syntax to describe the semantics of actions used in STRIPS. Pre- and post-conditions describe the applicability and effects of the actions [FL03].

It was decided early on to separate the parameterized actions, which represent the domain behavior, from the description of the objects, the initial state and the defined goal, which in turn represent the problem instance. Thus, a planning problem consists of a pairing of domain and problem description [FL03].

The language forms the basis for the scientific development of planning. It is useful as an expressive basis and enables the further development of realistic applications. PDDL has been further developed and modified in order to solve more complex tasks which are expected from autonomous planning and scheduling techniques [FL03].

2.4 Temporal and numeric planning

International planning competitions have often been a decisive motivator for scientific advances in planning since 1998. In order to approach realistic use cases new goals were set. In 2002, the third international planning conference posed the challenge of dealing with temporal and numeric resources. This provides the foundation for research into a modeling language that can express temporal and numerical properties of planning domains. The resulting developed language based on PDDL was PDDL 2.1 which adds numeric extensions and continuous durative actions. Numbers provide a domain with the ability to measure the use of critical resources and other parameters. For example, the energy consumption can be minimized as a modeled metric differing from the makespan, which describes the entire execution time of the plan, used so far in PDDL [FL03].

2.5 Planners

In addition to the PDDL, which describes the planning problem, an AI planner is the second important part in the autonomous planning process. The AI planner can read the PDDL, decomposes the problem and tries to solve it. There are many kinds of AI planners. From time to time new planners are released to cover new, specific use cases [GRM+].

2.6 Comfortable temperature

Objectively, the sense of well-being in terms of temperature is usually very different for different people. This makes it difficult to define an exact optimal value.

In order to still define a comfortable room temperature, a zone is defined, based on the thermal comfort in naturally ventilated buildings of the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 55. By analyzing 21,000 sets of raw data compiled from field studies in 160 buildings located on four continents in various climatic zones, de Dear and Brager created a bandwith describing the optimum and an acceptability of the indoor temperature [DB02].

According to the ASHRAE Standard 55, the optimum indoor comfort temperature T_{comf} depends on the mean outdoor temperature $T_{a,out}$ and is defined by

$$T_{comf} = 0.31 * T_{a,out} + 17.8$$

U get a 90% accaptability for 5°C band around the optimum comfort temperature T_{comf} and still an 80% acceptability fo 7°C band around the optimum comfort temperature T_{comf} [DB02]. A visualization of the bandwidths with a mean outdoor temperature between 10°C and 33°C is displayed in Figure 2.1. The comfort zone band for 90% acceptability will be used as the goal for the system of this thesis.

2.7 Importance of ventilation during the COVID-19 pandemic

In December 2019, a new type of respiratory disease was discovered, which was given the name COVID-19. The outbreak of this disease posed critical challenges for public health, research and medicine [FLR20].

The virus can be transmitted in various ways, for example in the form of liquid particles that arise when a person coughs, sneezes, sings, breathes heavily or speaks. These particles may be inhalated or ingested through mouth, nose or eyes. Infection via aerosols is also possible, especially in closed, overcrowded or rarely ventilated rooms. In these cases, regular ventilation can drastically reduce the risk of COVID-19 infection [PJ21].

The virus of the disease COVID-19 is called severe acute respiratory syndrome coronavirus type 2 (SARS-CoV-2). It is exhaled as an aerosol by COVID-19 infected people along with CO2. CO2 has been suggested as an indicator for regular ventilation since the 19th century and for some time now as an indicator for COVID-19 and other respiratory diseases. CO2 is exhaled together with

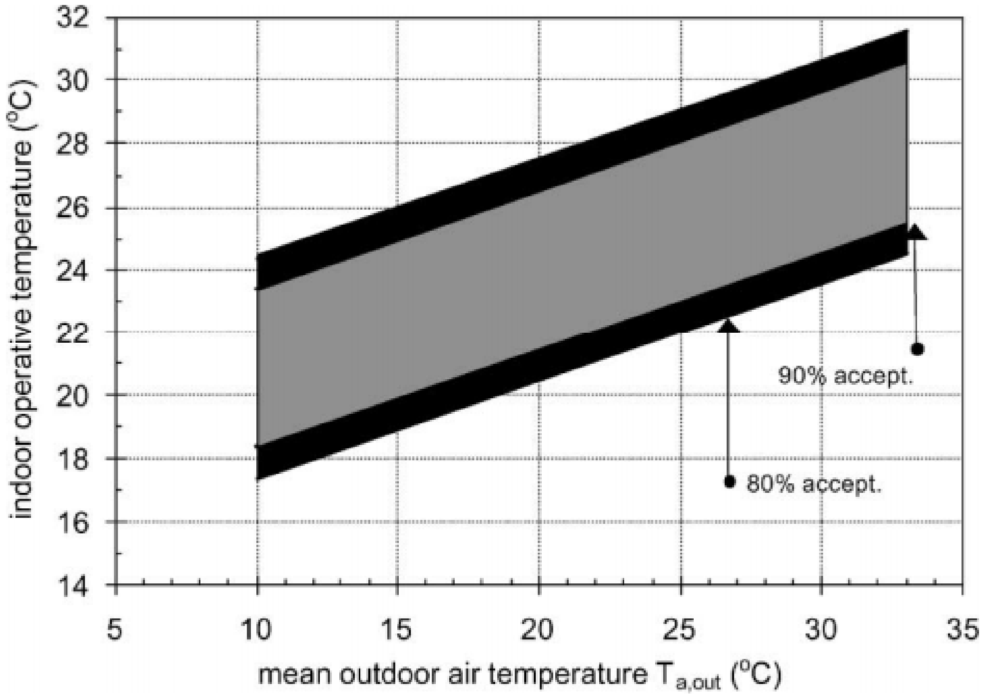

Figure 2.1: "Proposed adaptive comfort standard (ACS) for ASHRAE Standard 55, applicable for naturally ventilated buildings"[DB02]

aerosols containing pathogens. While the ambient CO2 content remains almost stable, the excess CO2 in closed rooms can be inferred from the origin of human exhalation. CO2 sensors are also inexpensive and can be used as indicators of infection risks and for mass use [PJ21].

The CO2 content of the outside air is approximately 400 ppm. The "Berufsgenossenschaft Holz und Metall" recommends a maximum CO2 content of 1000 ppm (pettenkofer number) for interiors. This value is often exceeded by far in closed, filled rooms (e.g. conference rooms) and the risk of infection is thus significantly increased [Ber].

3 Design of the solution

In this work, a system should be developed, which creates a Planning Problem with IoT Data from various Sensors deployed in different rooms of the company SPIRIT/21. The system then should be able to create a plan to get towards both, a comfortable temperature and a healthy CO2 value. The plan should then be saved in a database. This chapter introduces the basic design of this system.

3.1 Design

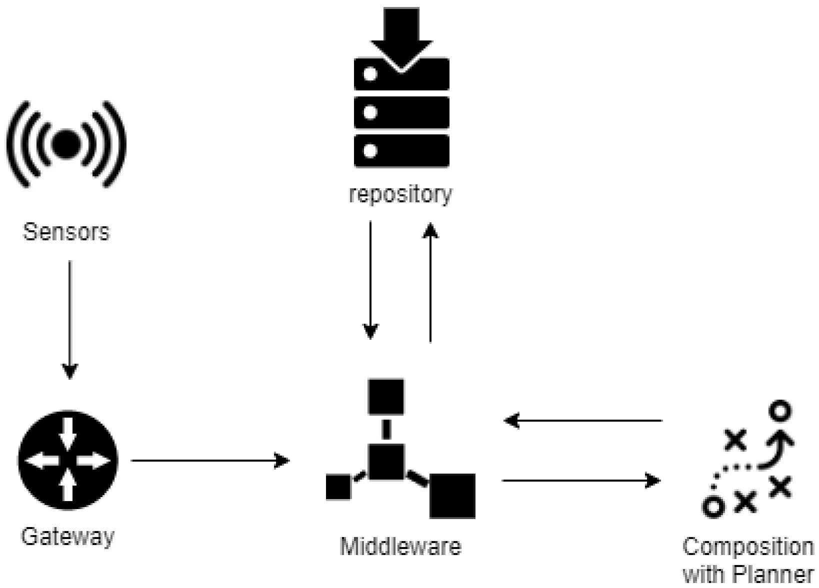

Figure 3.1: High Level Overview of the architecture design

Figure 3.1 shows a high-level overview of the architecture design, including the main components and interaction among them.

Every device has some kind of interface for communication. The sensors measure the interior values, which are then collected by the gateway. The middleware is used to bring the data directly into the repository, where the data is stored for further use. The composition part communicates with the middleware to retrieve the stored sensor data. A plan is then calculated and sent back to the repository.

3.2 Sensors and gateway

According to Palensky and Dietrich, improving energy efficiency in buildings begins with gathering information and insight into the processes involved. Data acquisition infrastructure forms the basis for gathering various data from the building environment. While the sensors gather the data about the ambient context of the environment, the gateways offer the application service to manage the sensors. The gateway service reads information from the sensors and joins the data into only one standardized message. It also provides an interface for upper layer components.

3.3 Middleware

The middleware integrates web services, APIs and devices quickly and easily into existing IT. It is used for the communication between gateway, repository and the composition.

3.4 Repository

The Repository offers services to store and retrieve data. In this context of use, the repository has to store the information, gathered from the sensors about the environment, as well as the plan which will get computed. The data can be stored in any type of database. Anyways, the choice can matter. NoSQL databases for example grew in popularity because of the ease of access, speed, and scalability [LM13].

3.5 Composition

The composition of this work consists of modeling planning problems of specific environments, solving these by executing a suitable AI planner and then storing the solution in a standardized format. Furthermore, a planning domain model has to be defined, which the problems can be solved with.

The developed system data flow is visualized in Figure 3.2.

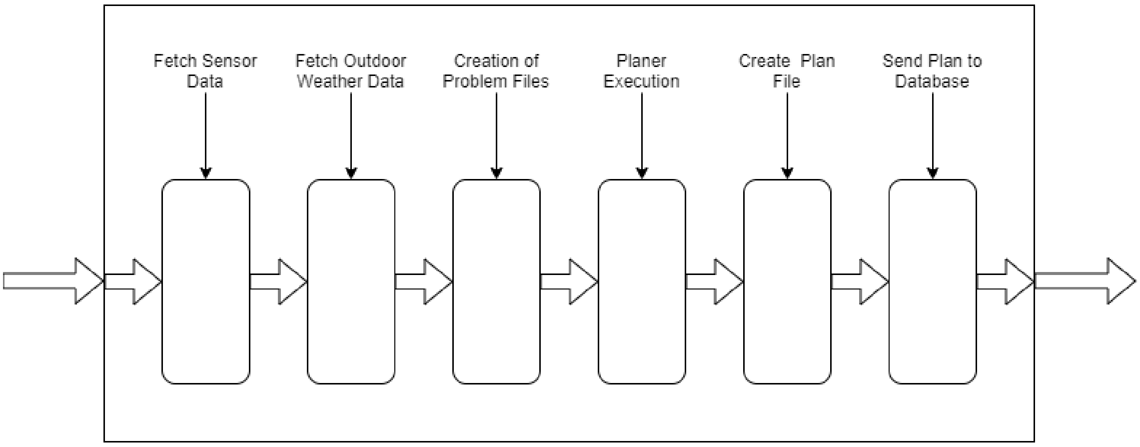

Figure 3.2: System Data Flow of the planned System

4 Implementation

This chapter provides details for the implementation and realization of the system developed.

4.1 Sensors and gateway

In the company SPIRIT/21 IoT ELSYS ERS CO2[1] sensors were placed in 12 different rooms. The data collected by those sensors, including temperature, humidity, light, motion and CO2 values, is sent to a Kerlink Wirnet iFemtoCell Gateway[2]. Due to power saving reasons, the data gets uploaded periodically (every 2 minutes).

For the company has no sensors outdoors, the OpenWeatherMap (OWM) API is used to gather information about the current and mean outdoor temperature.

4.2 Repository

As Database, the NoSQL database Elasticsearch[3] is used. NoSQL databases may deliver faster performance for systems involving time series or data coming from thousands of sensors. Although there are only a few sensors so far, the architecture is designed to scale. Anyways, the amount of sensor data saved in this database is huge. For Elasticsearch is optimized to find certain key value pairs, Elasticsearch is the option to choose. This allows to record and review the behaviour of the environment at any given moment in time.

4.3 Middleware

As middleware, SPIRIT/21's solution Node/21 is used to connect Gateway, Repository and Composition. It is ideal to develop IoT and Cloud solutions. Node/21 is used for three different processes in this work: (1) sending the gathered data of the gateway to the Elasticsearch database; (2) giving access into the Elasticsearch database by querying the data and offering it by an API in JSON[4] format; (3) saving the solution data into the Elasticsearch database by offering an API PUSH Method.

[1] https://www.elsys.se/shop/product/ers-co2-v1-5/
[2] https://www.kerlink.com/product/wirnet-ifemtocell/
[3] https://www.elastic.co/elasticsearch/
[4] www.json.org

4.4 Composition

The planning domain and planning problems are described by PDDL. The problem files include the initial state and goal state with respect to the elements defined in the corresponding domain file. Both files together are provided as input for the temporal planner.

4.4.1 Planner

Numeric variables with wide-range values are common in ubiquitous computing. Examples for such variables are temperature and location [KWLA13]. Since temperature is also used in our use case, the support of numerical variables from the planner is considered as essential. The OPTIC planner was considered as suitable planner for the problem as it can handle numeric variables as well as temporal metrics.

The OPTIC planner builds on the planner POPF, which was presented at the Twenty-Second International Conference on Automated Planning and Scheduling (ICAPS) and solves problems using Forward-Chaining Partial-Order Planning. The POPF Planner is already well-suited for solving time-related problems. It also supports the minimization of several preferences and not just of the makespan. The OPTIC planner supports both discrete models of PDDL and continuous models of the POPF planner [BCC12].

Regarding our problem, the minimization of the makespan is not always the best way to reach the goal. For example is cooling by ventilation prefered over using faster cooling by an air conditioner (AC) because of less energy costs and a better energy efficiency. For this the POPF and the OPTIC planner are equally suitable. We decided to use the OPTIC planner.

4.4.2 Domain

In this thesis, the domain is encoded as a room with three different devices, which are all subtypes of the type `object`. Every room has a `cooler`, an `heater` and `windows` to control temperature and CO2.

We're assuming that each room contains one of these objects and so 3 constants are generated that are used to work with in this domain. Having two or more Windows, ACs or heaters would just add a corrective factor to our model.

The three objects can interact with boolean variables as predicates that can change their state. They have the same function twice, in a positive and in a negated variant, since the OPTIC Planner does not support negative preconditions. An example of such predicates is `(heat-on ?a - heater)` and `(heat-off ?a - heater)`.

Also the domain can change its state using predicates. The predicate is required in a positive and negative form as well as the boolean variables above. These states are necessary to carry out actions after corresponding durative-actions got carried out. An example would be `(cooling-goal)` and `(not-cooling-goal)`.

Data	Function Name	Provided by	Needed for
indoor temperature	`temperature`	sensor	initial state
indoor co2	`co2`	sensor	initial state
outdoor temperature	`outerTemperature`	OWM	initial state
minimal indoor comfort temperature	`min-temp`	calculated like described in Section 2.6 with the mean temperature provided by OWM	goal state
maximal indoor comfort temperature	`max-temp`	calculated like described in Section 2.6 with the mean temperature provided by OWM	goal state
total cost	`total-cost`	calculated by actions of the planning domain	finding the most optimal solution

Table 4.1: Overview of data represented in domain functions used for planning

Numeric variables, modeled as domain functions, return the value of the variable they represent [GNN+17]. These variables are associated with the data gathered by the sensors and OWM. Also, the total cost of the plan is represented in the variable `total-cost`. An overview of the domain functions is given in Table 4.1.

Another numeric variable implemented is `people-in-room` which describes the number of people which are currently inside the room. Because there is no sensor installed to count the people in a room yet, it is statically set to *3.0*. This number impacts the development of the variable `co2` in every action to simulate the exhalation of aerosols (for every person in the room the `co2` value increases by *8.0* [GLC10]).

There are three main actions which are possible in this domain which are `ventilation`, `cooling` and `heating`. These actions cannot be performed at the same time due to ineffectiveness. Furthermore, the action ventilation is divided into `ventilation-heating` and `ventilation-cooling` on the basis of to the different behavior in relation to indoor and outdoor temperature.

The actions are divided in `durative-action`, which describe the duration of the action and its effects on devices, and actions, which will change the domain functions. It's not possible to change numeric variables in durative-actions with the OPTIC planner.

The duration of the durative actions has been statically set to *1.0* to represent 1 minute. It is not possible to make the duration variable and refer to this variable duration in the following action. The longer the duration of the actions, the more efficiently the planner will run, but the solution will be less precise.

While the planner runs, the actions have an effect on some variables, which are mentioned in Table 4.1.

Estimating the effects on temperature and CO2 change proved to be quite difficult. Not only information such as room and window size, heating and air conditioning performance etc. were not included in the problem, temperature and CO2 also approach the outdoor values exponentially and are therefore not linear.

Estimations to describe the effect were made by evaluating different field studies [KDL14; LH08; LPK20; Ram; Smi]. The resulting effects are shown in Table 4.2.

Additionally, the action `change` was implemented to add costs for changing an action, for example from ventilation to heating, to simulate the effort to open/ close windows and the additional costs incurred by starting up the AC or the heating.

Action	Effects
ventilation-cooling	**increase** `total-cost` 1.0 **decrease** `temperature` 0.01 **decrease** `co2` 16.0
ventilation-heating	**increase** `total-cost` 1.0 **increase** `temperature` 0.01 **decrease** `co2` 16.0
cooling	**increase** `total-cost` 7.0 **decrease** `temperature` 0.06 **increase** `co2` 24.0
heating	**increase** `total-cost` 7.0 **increase** `temperature` 0.06 **increase** `co2` 24.0

Table 4.2: Overview of the effects caused by the actions of the domain

A simplified representation of the possible actions is given in Figure 4.1.

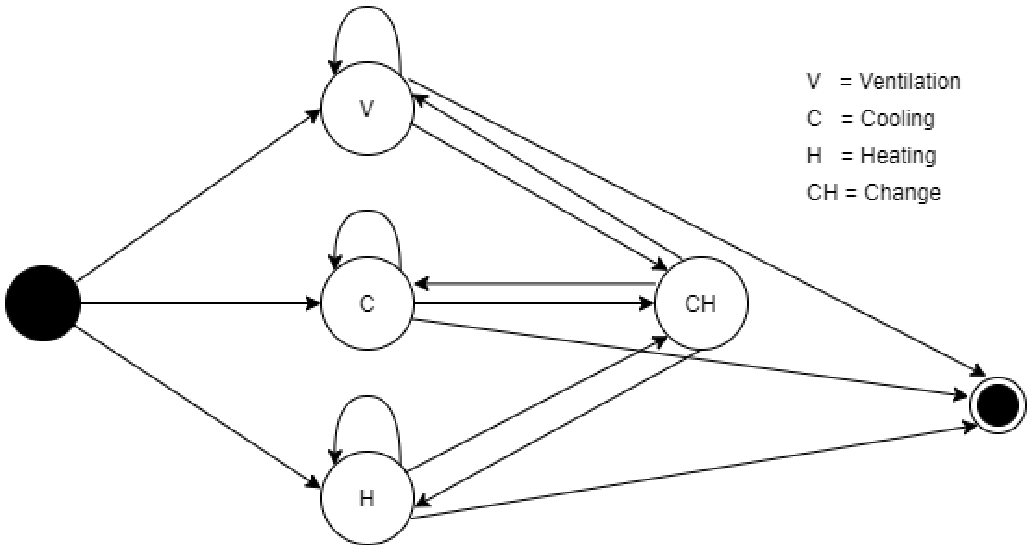

Figure 4.1: Graphical representation of the actions possible in one room

As already mentioned in Section 4.4.1, the OPTIC planner does not minimize the makespan, but rather the numerical variable `total-cost`. Depending on how the various actions are prioritized, based on energy costs, efficiency and convenience, the `total-cost` variable is increased.

4.4.3 Problem

The problem file is automatically generated by a Python[5] algorithm using all the latest sensor data fetched from the middleware. The file describes the initial state, the goal and the metric to minimize. The initial state contains the configuration of the boolean variables and the sensor data. Without the configuration of the boolean variables (everything is assumed to be turned off and the windows are assumed to be closed), the main part of the problem file is displayed in Listing 4.1.

```
(:init
  (= (people-in-room) 3.0)

  (= (temperature) 22.5) ; [degC]
  (= (outerTemperature) 20.55) ; [degC]
  (= (co2) 479) ; [ppm]

  (= (total-cost) 0.0)
  (= (min-temp) 20.48) ; [degC]
  (= (max-temp) 25.48) ; [degC]
)

(:goal
  (and
    (< (temperature) (max-temp))
    (> (temperature) (min-temp))
    (< (co2) 800.0)
  )
)

(:metric minimize
  (total-cost)
)

```

Listing 4.1: PDDL problem example

The `:goal` describes the temperature in the 90% acceptance percentile, as discussed in Section 2.6 and the `co2` value under 800 ppm, which is less then the minimum threshold described in Section 2.7. As mentioned, the value `total-cost` is minimized.

4.5 Input and output

The OPTIC planner takes the problem and domain file described above and calculates the best possible solution. To manage a connection from the planner to the middleware, a Python environment is used. To start the calculation, the user only has to start the `main.py` script with the name of a specific room or `all` for the calculation of all rooms as argument.

[5] https://www.python.org/

4.5.1 Input

To get the sensor data into the problem file, it has to connect to the middleware. Python is used as the programming language due to its simple and good asynchronous usage. With the Node/21 framework, API interfaces can be created easily. They return data from the ElasticSearch database in JSON format. Also the OWM data can be fetched by an API get request. The JSON data can now be transformed easily into variables which then can be placed in the problem file. The planner can calculate the solution with the generated problem file.

4.5.2 Output

The management of the output of the OPTIC planner was not trivial, for no output file gets generated, as it gets by the POPF planner, but the solution will be displayed in the console. As a workaround we fetched the console output into a text file and transformed it into a readable JSON file. The JSON file has the format displayed in Listing 4.2, which should be easy to visualize and work with. The JSON File can be saved in ElasticSearch by using the API interface offered by Node/21.

```json
{
  "forecast_data": [
    {
      "timestamp": "2021-06-15T19:40:27.582Z",
      "temperature": 26.3,
      "id": 0,
      "co2": 326
    },
    {
      "timestamp": "2021-06-15T19:45:27.582Z",
      "temperature": 25.3,
      "id": 1,
      "co2": 446
    }
  ],
  "actions": [
    {
      "startTime": "2021-06-15T19:40:27.582Z",
      "endTime": "2021-06-15T19:45:27.582Z",
      "action": "cooling"
    }
  ],
  "roomname": "ebusiness"
}
```

Listing 4.2: Example of a JSON Output

4.6 Deployment on AWS

Since many customers of SPIRIT/21 have their resources partly or fully deployed in the cloud, it was decided to run this system in the cloud as well. Due to internal company preferences, the decision was made to use the Amazon Web Services (AWS) public cloud[6]. An EC2 instance was set up for this in which the planner as well as the Python and PDDL code were inserted. The use of the virtual machine in the cloud provides access through cloud-native applications such as AWS lambda[7] using security standards offered by the cloud.

[6] https://aws.amazon.com/

[7] https://aws.amazon.com/lambda/

5 Validation, evaluation of solution

5.1 Deployment

The sensors are delpoyed in 12 rooms of SPIRIT/21's office building in Böblingen (48°40′48.56″N 8°58′20.61″E), Germany. The IoT Data is displayed on tablets using the tool Grafana[1] as shown in Figure 5.1[2].

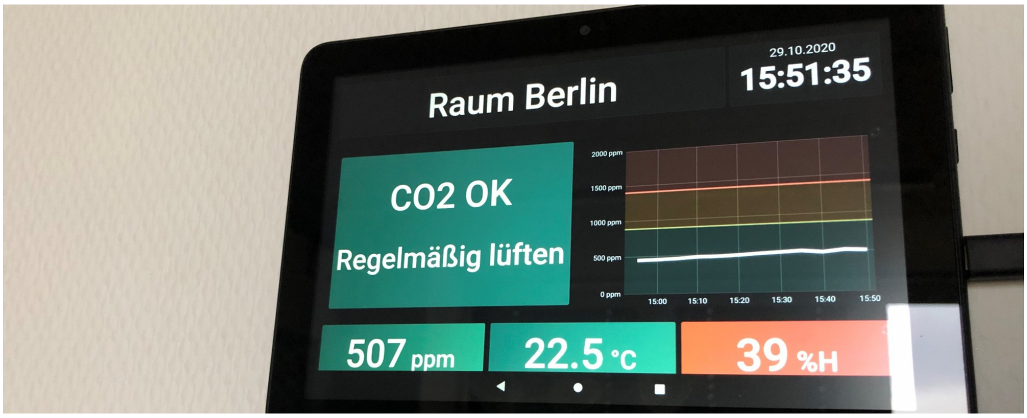

Figure 5.1: Grafana visualization of the IoT Data gathered in a SPIRIT/21 meeting room

5.2 Execution

The execution of the Python script works well and delivers solutions which reach the goal by reducing the `total-cost` variable. The runtime of the planner to solve the developed domain and plan depends on the states evaluated. Number of evaluated states and runtime of the planner are approximately linear to one another as shown in Figure 5.2. However, the states evaluated depend on the total-cost. The relationship between `total-cost` and states evaluated is almost logarithmic as displayed in Figure 5.3.

The tests were carried out by a virtual machine running Debian 10.x operating system with 2GB of RAM.

[1] https://grafana.com/

[2] https://spirit21.com/blog/smarte-iot-loesung-gegen-dicke-luft-wie-das-raumklima-automatisiert-ueberwacht-werden-kann

Figure 5.2: Comparisson of the states evaluated and the runtime of the planner

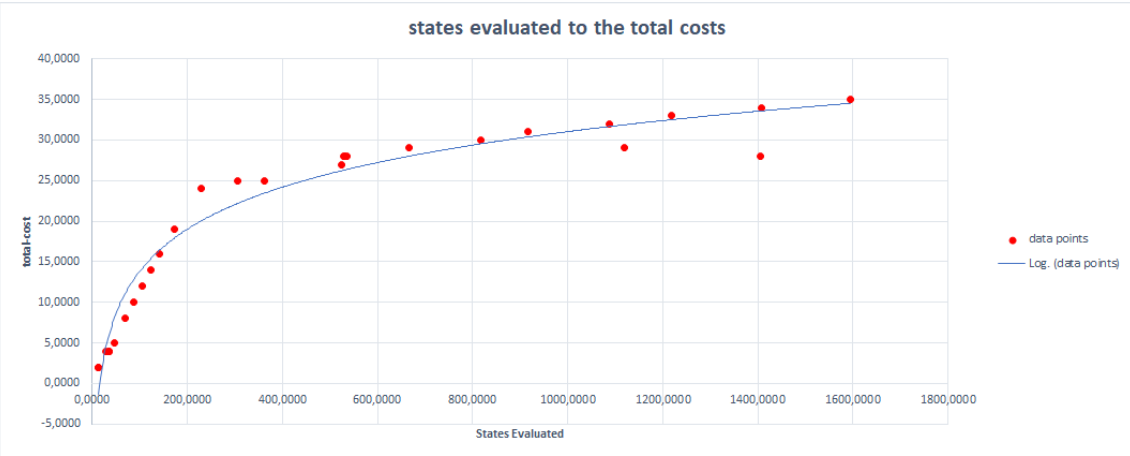

Figure 5.3: Comparisson of the states evaluated and the total-cost variable of the planner

5.3 Visualization

The system developed in this thesis calculates realistic solutions depending on the outdoor temperature considering ventilation as action to cool or heat the temperature and to decrease the CO2 value. The consideration of ventilation lowers the time of needing an AC or heater which increases energy efficiency and lowers the operating costs.

However, the temperature is assumed to change linearly by the actions. This is a simulation of the indoor temperature approximating the outdoor temperature. Nevertheless, the indoor value actually approximates the outdoor value, following the heat equation by Fourier [CN47].

The outdoor CO2 value does not change significantly over the day. National Oceanic and Atmospheric Administration (NOAA) regularly publishes the CO2 values of the atmosphere. According to their measurements, the average value in May 2021 was 419.13 ppm [NOA]. For the CO2 can't be too low, only an upper threshold is set. The indoor value gets managed by ventilation and gets increased by the number of people in the room (at the moment statically set to 3). Especially during the

COVID-19 pandemic the importance of a low CO2 value increased due to its correlation to the aerosols exhaled, possibly containing the virus, as mentioned in Section 2.7. The system makes sure, that the value is always under 800 ppm at the end of the plan. This results in a good and healthy air condition.

Overall the solution ensures a comfortable temperature and an healthy CO2 value in the meeting room considering ventilation as a tool to save energy costs and lower the emissions.

Example solutions are visualized in Figure 5.4 and Figure 5.5. Figure 5.6 displays a rule-based approach, using the same initial state used in Figure 5.5, which tries to satisfy the following rules: (1) CO2 has to be reduced by ventilation, when satisfied, follow rule 2; (2) temperature has to be increased/ decreased to the comfortable zone using heater or AC. The satisfaction of the rules is checked every minute.

The comparison of Figure 5.5 and Figure 5.6 shows the obvious advantage of the planned solution compared to the rule-based solution. The solution using the AI planning system halves the time using an AC leading to an improved energy efficiency. Besides, the makespan to reach the goal is reduced significantly.

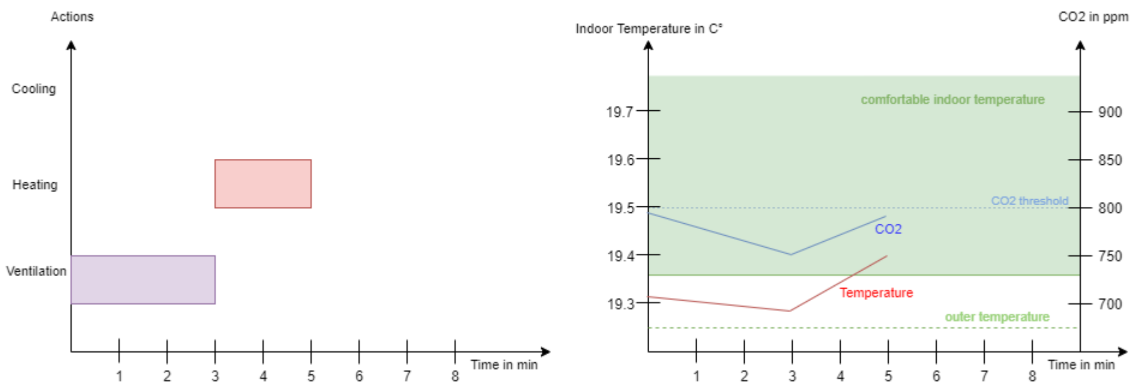

Figure 5.4: Example solution calculated by the planner using ventilation and heating to increase the temperature and decrease the CO2 value to a comfortable and healthy level

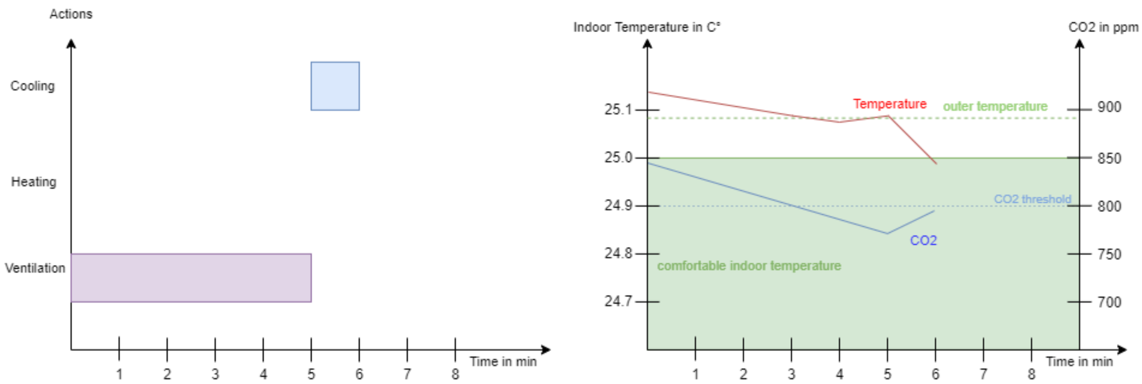

Figure 5.5: Example solution calculated by the planner using ventilation and cooling to decrease the temperature under the outdoor temperature and decrease the CO2 value to a comfortable and healthy level

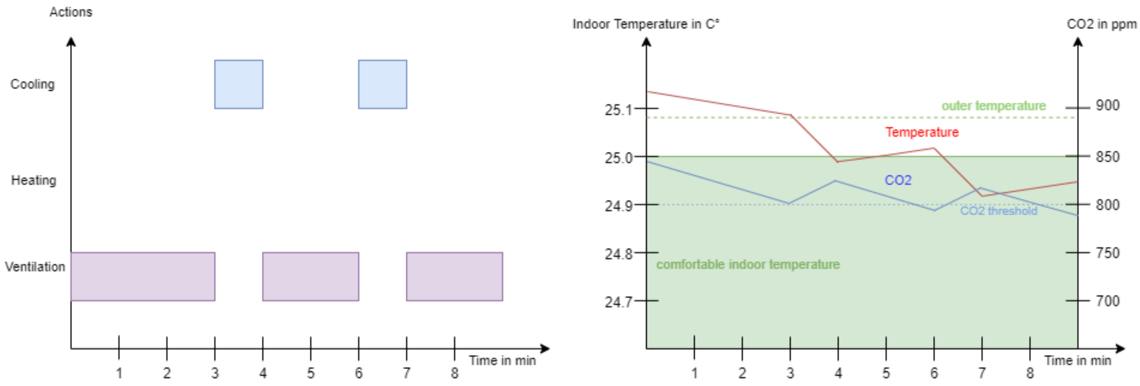

Figure 5.6: Example execution by a rule-based approach using ventilation to lower the CO2 value and heating and air conditioning to set the temperature to a comfortable level

6 Conclusion and outlook

6.1 Conclusion

Non-residential buildings make up about 25% of all buildings in europe. The energy saving potential in this sector is considerably high due to the typically high energy consumption [DCB17]. “The energy transport grids might soon face their limits, and intelligent DSM is one way to stretch these limits a bit further” [PD11]. DSM, including the optimization of energy efficiency, has the potential to reduce both emissions and operational costs.

A potential problem is the management of the temperature and CO2 with AC, heater and ventilation. The thesis shows an approach to solve this problem by using IoT systems and AI planning to anticipating a solution using the IoT setup of SPIRIT/21. This includes the integration of sensor data into a PDDL problem file, the implementation of a PDDL domain representing the office room and the storage of the solution calculated by the OPTIC planer.

The calculated solutions show, that ventilation can often reduce the time of using an AC or an heater. At the same time a CO2 value below 800 ppm is ensured after running the system.

The developed system shows the potential to use AI planning in different complex real life situations for DSM.

Also, this system can be used as foundation for future systems as further described in Section 6.2.

6.2 Future work

6.2.1 Evaluation by field study

The evaluation by visualizing plans was a fist step. The next step would be to implement real device operations to follow the plan calculated. This can be used to proove the usability of the system. It also allows some fine-tuning of variables beyond the simulation.

6.2.2 Developing the system

This thesis shows an approach to solve DSM Problems by using IoT systems and AI planning to anticipate a solution. Nevertheless, the system can be developed further. Some thoughts are listed in this chapter.

Soft deadlines

For the OPTIC planer also supports defining soft deadlines, it would be possible, for example, to prioritize a comfortable temperature with 80% acceptance over an acceptable CO2 value. The other way round the CO2 value could be prioritized over a comfortable temperature.

Adding variables and constants

More variables and constants can be inserted to develop the system further. This will lead to a better anticipation. As mentioned the current number of people in the room can be an input delivered by person recognition sensors. Also, the weather and humidity are factors which can be added to the problem file. Information like the size of the room, or the size of the windows can be implemented as constants. This will help to anticipate the costs for heating and cooling by devices as well as the time needed to cool or heat a specific room through ventilation.

Improve anticipation

As mentioned in Section 5.3 the anticipation of the CO2 value and temperature has to be further evaluated. An idea is to use the difference of the outer (v_{outer}) and inner (v_{inner}) value to create an approximation to the inner value:

$$v_{new} = \frac{v_{inner} - v_{outer}}{x}$$

Adding more rooms

Another way to develop the system would be to let the different rooms interact with each other. A use case would be cross-ventilation, which increases the speed of cooling or heating and the lowering of the CO2 level by ventilation. Therefore, also doors have to be implemented.

6.2.3 Trying another approach

We used a language derived from PDDL to define planning domain and specific problems to it. Another possible language is used in Hierarchical Task Networks (HTN), which works with sets of tasks. A planning approach using HTN planning might be better suited or more beneficial then PDDL because it is faster and more scalable when applied to real-world problems [GA15].

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