With all the great technology humans have developed over the last decades, it is easy to think that we are in control of everything. Often, the influence of natural catastrophes like tsunamis or wild fires is overlooked. An example for this is the Fukushima disaster in 2012. The nuclear power plant was located at the coast without planning for an unlikely but possible tsunami occurrence (world\_nuclear.org, 2018) Accidents like Fukushima brought the need of accurate simulations that can predict natural causes’ influence well in advance – preferably before power plants or factories are even built.

The advantages of Cellular Automata (‘CA’) were soon noticed and have since been widely used. They allow for large parameter spaces to be modelled. For example, a 2D-CA with 13 cells has 2169 possible configurations. CA are able to plot form, function, pattern and process a scenario including time and inter-cellular relationships (geography.name, 2018).

The task was to simulate a wild fire over a terrain made of chaparral, a dense forest, a canyon containing scrubland and a lake. The town close to this area is in need of a reliable simulation of a wild fire spread to account for the possible malfunction of the nearby power plant. Furthermore, a waste incinerator is proposed to be built and poses an additional ignition threat. There have been several research projects on the implementation of accurate CAs for wild fire spread in the past that can be used to obtain a well-informed overview of the topic.

The Department of Mechanical, Chemical and Materials Engineering at the University of Cagliary and the Institute of Biometeorology of the National Research Council in Italy developed a CA with a, “to a raster-based approach” comparable computational cost but without its limitations. Their study is titled ‘An Improved Cellular Automata for Wildfire Spread’. Raster-based approaches struggle to take the distortions that affect a fire’s shape into account. The CA approach also allows for more accuracy in showing the realistic velocity of a fire’s spread. The research group used correction factors to improve the CA’s performance such as the use of several optimization algorithms which were used to reliably show the impact wind has on a wild fire. They came up with models of fire-spread shapes under various different conditions (Ghisu et al., 2015).

Another conducted study in the field of wild fire simulation (Clarke, 1994) published 25 years ago may seem outdated and irrelevant to some. However, it still manages to give a respectable insight into the CA approach and includes well explained details on a fire’s physical and chemical processes. Determining the different fuel resource parameters is difficult without consulting an expert on the topic. The study gave a comprehensible introduction to their approach of taking different terrains into account: ‘Monte Carlo techniques were used to provide fire risk probabilities for areas where fuel loadings and topography are known. The model assumes predetermined or measurable environmental variables such as wind direction and magnitude, relative humidity, fuel moisture content, and air temperature. During the fire, the reaction itself is strongly influenced by the type and distribution of the fuels, the fastest fuel to burn, and with the greatest intensity were the fine fuels such as leaf litter, pine needles, and grass. Wood burns comparatively slowly, since the critical ratio seems to be the total surface area exposed rather than the type of fuel material.’ (page 1355 - 1356). The model was tested using data from the Lodi Canyon Fire in 1986. The simulation produced a 82.5% accurately predicted fire map calculated on a pixel basis.

To initiate a CA, the terrain was first set on the initial grid. Each cell was assigned a type of terrain – either lake, chaparral, canyon or dense forest based on the location of the cell. At a later stage, cells representing the location of the town were also introduced. The latter states 5-8 were just for visual purposes, representing if a material is burnt-out and the town. These visual states were not assigned ignition likeliness or burning duration parameters.

The number of states needed for the actual fire spread simulation was considered. The study introduced in the above literature review section - ‘An Improved Cellular Automata for Wildfire Spread’(Ghisu et al., 2015) – used four states:

* Unburnable
* Flammable, but currently not ignited
* Flammable and ignited, but the fuel hasn’t been fully consumed yet
* All fuel in the cell has been consumed

An approach similar to the above does make sense for the given task also, since the terrain includes an unburnable lake and flammable chaparral, canyon and dense forest ground. For simplicity, the use of only three states: healthy - 0, burning – 1 and burnt – 2 was chosen.

For visual purposes, 9 states – healthy lake, canyon, chaparral and dense forest; burning; burnt out canyon, chaparral and dense forest and the town, were used to more closely replicate the map given in the task brief. This made it possible to display the different colors for each terrain and makes it easier to follow the fire spread and cellular interactions. All the healthy and burnt out states are treated the same way inside the program, no matter what terrain they belong to.

The grid is initialized, and then a starting point for the fire is selected. This can be done within the user interface and also allows for the possibility of multiple fire origin points as well.

Once the initial state of the map is finalized by the user and the CA configured and ran, each terrain gets assigned a likeliness to burn. To make sure did not start burning, any cell that was assigned as a lake cell had no possibility to ignite. To make the simulation as realistic as possible, several studies comparing the likeliness to burn of chaparral, canyon and dense forest grounds were found (Engstrom et al, 2004). Unfortunately, the terrain’s likeliness to burn depends on a lot of external factors e.g. temperature, humidity, the flora’s density and previous fires. Due to the limited time available, the introduction of external factors such as these were not included.

A study states the comparison of likeliness to burn between different types of leaves, grass and wood (Ghisu et al., 2015). The group then researched what kind of plants the different terrains are made of. Chaparral and canyon lands are usually found in North-West America so focus on studies referenced were studies from that area as they are the most similar to the given task.

Chaparral grounds consist mostly of grass and some bushes or pine trees (Blueplanetbiomes.org, 2018). Therefore, it has the highest likeliness to catch on fire.

Canyons containing scrubland grow in dry and hot climates, especially in the USA. This results in vegetation compromising of dry grassland with rare occurrence of small pine or oak trees (Animals.sandiegozoo.org, 2018). According to this, the canyon’s likeliness to burn is even higher than the chaparral’s.

Dense forests are mainly wood material thus do not catch on fire easily.

A terrains likeliness to burn was done by picking a random number within a set range, the smaller the range, the more likely the cell is to catch on fire. Thus, every cell in the terrain has a different likelihood of ignition, although some cells are part of the same terrain. The randomness simulates the varying density, humidity or occurrence of trees and makes the simulation look more realistic. After running several test simulations with varying ranges for each terrain, a random number from 0 to 3 was found to be appropriate for the canyon, 0 to 8 for the chaparral and a range of 0 to 15 for the dense forest (see Figure A1).

In the next step, the different terrain types get assigned a duration parameter describing how long it takes until a cell of that terrain type is burned out / all the fuel in the cell is consumed.

The problem brief stated how long each area is roughly burning for:

- Chaparral: several days

- Canyon: several hours

- Dense forest: up to one month

According to these values, a logical choice was made to proceed in time steps, equivalent to intervals between generations in a CA approach, of one hour each and allow for consistency throughout the whole CA.

Once all these parameters are set, the transition function is then run. This function calculates if a cell's state is going to change in the next generation depending on the states of its neighboring cells sates and the cell's parameters (likeliness to catch fire and burning duration).

A cell ignites in the next time step if at least one of its direct neighbors is burning and if the random value indicating its likeliness to burn is small enough (lower than 1).

A cell is burning out in the generation if it is on fire and has been burning for as many hours as assigned to its terrain's burning duration.

The strength and wind direction was also taken into account, with wind blowing in a direction the fire spread increases the cell's likeliness to catch on fire if the cell stated in the wind direction is on fire.

Regrowth of terrain was taken into account, but was decided as impractical as chaparral and scrubland need several months to start growing back and years to fully regrow. Forests require several years (Californiachaparral.com, 2018). Also, the regrowth process is heavily influenced by the frequency of fires. Nowadays there are more fires than most ecosystems can handle leaving behind dramatic damage.

The line of action of our CA can be reconstructed in the following figure.

3.1 Testing the parameters

To simulate the wild fire in the most realistic way possible and return a reliable system to our client, several tests were conducted.

Multiple simulations with varying the burning durations of each terrain were conducted. For the chaparral we experimented with values between 96 and 192 hours (4 and 8 days), for the canyon with values between 4 and 30 hours and for the dense forest with values between 672 and 792 hours (28 and 33 days). We ended up picking 120 hours (5 days) for the chaparral, 20 hours for the canyon and 720 hours (30 days) for the dense forest. These values seemed the most realistic in terms of their proportions and were convenient to follow in the graphical simulation as well.

Next we were running tests to improve our way of implementing the wind’s influence on the fire. We started with a 3x3 wind matrix that mapped the wind strength onto the position where the wind is coming from.

North-West North North-East

West X East

South-West South South-East

The middle position X hereby indicated the current cell. For example, the matrix below would indicate a wind with force 3 coming from the North-East.

0 0 3

0 X 0

0 0 0

This allowed us to take overlapping or multiple winds with different strength into account. Nevertheless, this approach was computationally quite time-consuming and not practical in the further implementation process. Therefore, we alternated this approach to a simpler one assuming that we are only considering wind coming from one direction. The program now has a wind\_value and a wind\_strength. The first one keeps track of the wind acting on the current cell. The wind strength is a set parameter indicating the wind’s strength. The user has to comment out whichever direction the wind should be coming from (see Figure A2). In theory, the user can comment out two or more wind directions but they would all have the same strength and would add up to another while in reality they might weaken each other or change each other’s directions.

The wind\_value is increased by the wind strength when a neighbour cell in the wind direction, e.g. the neighbour cell north-east to the current cell, is burning. The wind\_value then gets subtracted from the cell’s likeliness to burn increasing the chances that the cell catches on fire (see Figure A1).

**ABSTRACT:**

The task given was to analyze how Cellular Automata-based Simulation can be applied to represent and investigate the spread of a forest fire. The officials of a fictional town want a CA-based model to explore potential forest fire spread in the region surrounding their town due to a potential threat of the nearby power plant and a proposed incinerator. To do this, the use of a python program CAPyLE was utilized to first initialize the structure of the region including, the canyon, forest, lake and the surrounding chaparral. The initial fire location can be set by the user and the way the fire spreads was done with a transition function which dictated the state of a cell within a 2D grid representing the map. If the fire starts at the proposed incinerator, it was found to take around 8 days to reach the town and if the fire started at the power plant, it would take 5 and a half days to reach the town. The main conclusion from the task given was that the town is in serious risk of being affected by a wild fire and safety measures are needed to reduce this risk.