ManEl

A mobile solution for electrical consumption management

Gazzola Francesco, Oscar Delaveau, Deema Lama

Innovation Communication Technology Entrepreneurship, ICTE2 - 2.4, 2020

STUDENT REPORT

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STUDENT REPORT

Aalborg University Copenhagen
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Semester Coordinator: Henning Olesen
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Semester:
Spring 2020

Title:
ManEl - A mobile solution for electrical consumption management

Theme:
ICT services: Design and Architectures

Project Period:
From 01-02-2020 to 25-05-2020

Project Group:
2.4

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Copies: 1

Page Numbers: 72

Date of Completion: 24th May 2020

Abstract:

In the recent years, people are getting constantly more concerned about climate change and the effect it has on their lifestyle. Sustainability has therefore become nowadays the epitome of this new way of living. For such reasons people have a growing interest in companies that help them living as an eco-friednly person by changing their habits.
In this report we present a mobile-based solution to help users manage their electricity wiser to avoid the overproduction of energy. In this work, we have focused on the prediction of the consumption of electricity by exploiting an intelligent algorithm. Moreover, we give a presentation of the interface we prototyped by taking advantage of UI principles in order to ensure the best possible user experience.

The content of this report is freely available, but publication (with reference) may only be pursued due to agreement with the author.

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Chapter 1

Introduction

The environmental situation of our planet is nowadays a priority that increasingly occupies our attention worldwide. The main reason for this lies in the fact that over the last few years we are all experiencing that the environment has been changing.
For instance, one could notice the average temperature of the earth has increased. This phenomenon, known as ‘Global warming’, doesn’t only affect the ecosystem, causing natural catastrophes, but it also has a huge impact on the economy and above all on our health [1]. All these consequences has made the climate change become one of the most important issues of our time [2].

The main contributor to global warming and consequently to get people worried is air pollution [3] [4]. It is mainly due to the activities related to energy production [5], since most of it is based on burning fossil fuels. As a consequence, a lot of countries nowadays are adopting renewable energy sources and a greater number of people have brought the sustainability concept into their daily life. Indeed, electricity represents a primary need for everyone in this digital world

and therefore, people can't give up using it. As a result, most of the consumers are now using it more wisely and would benefit from companies helping them live in a more sustainable way [6].
Company have taken advantage of this fact during these years and have developed several mobile apps for helping people to be more environmentally friendly.

The reason behind why company are offering mobile solutions instead of the web counterpart lies in the fact that worldwide more people access the internet from their mobile and tablet devices than from desktop computers. People depend on mobile devices every day for communications, eCommerce, content consumption, work, banking, directions and increasingly as their sole computing device. Moreover, a recent research shows that 90% of the time spent on smartphones is spent in apps and only 10% on browsing on the internet [7]. Furthermore, the number of downloaded app is continuously increasing and experts predict that there will be a 25% increase in global app downloads between 2018 and 2022 [8].
With this in mind, from a sustainability perspective, it's possible to see that applications that even have a tiny effect on the environment could result in a great impact if they are considered all together.
Given this last point and the massive amount of user, it comes naturally to drive one's attention toward the development of an app rather than a website.

Developing an application is not to be taken for granted. With the users having lots of choices and alternatives for products and/or services companies are offering them, designers have to develop it in some way to grab their attention. For this purpose, products need designing to make customers feel as much comfortable as possible in using it by so reducing the users' frustrations and the time they might take to understand how to use the application. Moreover, from a business's point of view, it's essential to emphasize on the users' satisfaction in order to build the brand value and reputation of the business [10]. These two aims at representing the main value User Interface and User Experience Design bring to a product.

All the considerations made so far have been taken into account in the work we are going to present through this paper. In this report we are giving a presentation of a mobile solution we came up with in order to allow users to use their electricity wisely. The main feature of this app is predicting the moment in which the production of electricity will be at the lowest in a specific city chosen by the user. For this task, we applied intelligent algorithms by exploiting machine learning techniques. Moreover, the final app interface has been designed firstly by taking into account some UX and UI practices and secondly by using feedbacks we collected by some interviews after a first prototype was developed. An important aspect to point out is the context we set ourselves in order to bring a real value to the forecast, which is currently widely used by many corporations of the field.

We put ourselves in a fictional context where we are working for a new distributing company that sales electricity to residential consumers. We are a department of the company that aims at developing a new tool to help people manage their electricity consumption. The offer proposed by this company is to price the consumers depending on an hourly evolution of energy production in the users area: if the production increases to satisfy the consumers' needs then price increases as well. On the other hand, if the production decreases then the price follows the trend. It is called the « Real Time Pricing ». This system pricing carries values of sustainability and cares about the pollution induced by energy production industry. Therefore, with our mobile solution the company would like to change its customers' behaviour by notifying them of the best times to consume less and thus avoid the excesses of consumption within their living area. Those excesses can lead to a need for more power plants to run and produce more energy which itself has direct consequences on environment. The factories needed for abnormal production are specific for this kind of uses and have several disadvantages: they don't run all year so it requires resources to turn them on and they cost and pollute more than usual factories do.

We start out presentation by first illustrating an overview about the state of art. We move on discussing the machine learning technique we used and then the UX principle and practices we adopted for designing the interface. The report concludes with the basic foundations of the system design needed for the service to be deployed.

1.1 Problem formulation

A greater number of people are currently worrying about global warming and the effects it has on the environment. People are aware of the side effects it could have on their health and wouldn't like to be just spectators of the crisis. Moreover, producing energy from polluting sources is one of the main causes related to climate change.
By taking all these ideas into consideration, we came up with the following question:

How can we help people to manage their electricity consumption for the sake of the environment ?

1.2 Delimitations

This work is an academic work that overlook a service in its technical aspects. Therefore it contains a few missing points that will not be discussed due to technical or time difficulties.

In this work we are not focusing on any economic aspects of electricity production or consumption.

We are not taking into account the kind of power sources that are being used to produce it.

The only parameter we are considering is the history of electricity production and not other important ones that can affect the electricity production or consumption such as : weather, cost of fuel, regulations.

We do not make the difference between the amount of energy produced and the amount of energy consumed (we do not take into account energy loss).

The data used for the machine learning algorithm are coming from the United-States and are for demonstration purposes only. Therefore the use of electricity might be biased compared to other regions of the world but we do not take that into account.

Another consideration, which is not to overlook, is related to the cities users can choose as inputs. In this work we considered only Danish cities. This choice was made to keep the project simple, while the country was chosen arbitrary.

The purpose of presenting a system design in the report is to lay a foundation for the implementation of the proposed app in the future. In our project, we are not implementing it, but only a non-functioning prototype. The user and system requirements have been specified but we are not discussing in the report how they will be fulfilled.

Chapter 2

Methodology

As a department of a fictional company distributing electricity through a new offer we needed to brainstorm on how to tackle the problem. We then decided to produce a research-based project, which aims at creating a conceptual application to forecast the electricity consumption by exploiting the state of the art of Artificial Intelligence, which is machine learning.

We started our project by first looking into how energy consumption could be predicted by a machine learning algorithm. To achieve this task, before starting to code, we needed data about the energy consumption as an input into our future algorithm. We took advantage of 'Kaggle' [9], an online platform, which is well-known among data-scientists for its huge number of datasets. Once we got the database, we started to analyse it to understand it in the most efficient way. Then we computed a machine learning algorithm to forecast electricity.

Once the intelligent algorithm was ready, we needed to display the results in the app. This task was carried out by looking at the existing apps as an inspiration for the interface of the app and by brainstorming: we placed ourselves as the

users of the app and thought about what the app could do and how the interface could look like. We therefore sketched the different screens of the app and then we turned them into a first digital prototype of the app.
As the draft of the interface was finished,we conducted open structured interviews. We asked to four users what they knew about the electrical energy to get an idea about how much people are really aware of the impact it has on the environment. Afterwards, we presented them the prototype and asked to them if they could figure out what the app was for. This request was enquired to get indirect feedbacks about how understandable and user-friendly the interface appeared. They were also asked to perform three tasks using the prototype. Their sequential steps while performing those tasks were recorded.
We then collected the feedbacks from all the participants and took them into consideration to improve our interface and thus creating the second prototype. In designing both interfaces we didn't neglect the UI and UX design principles and practices.

The final task was to organize and design the overall system architecture of the app. For this work, the client-server communication model appeared to be the perfect candidate to suit our needs. Every service which exploits artificial intelligent tools require high computational power and they are therefore run by a cloud platform. The database is being updated every hour once a new input of energy production (production and consumption are considered as the same) value comes in.

Chapter 3

State-of-art

As mentioned in the introduction, in the last few years a great number of sustainability related mobile apps have been developed. The tech-companies don't just aim at making a profitable business but mostly they look at influencing people's behaviour for eco-friendly purposes.

In a study carried out by some researchers of the Georg-August University [10], after conducting a comprehensive search process in Google Play Store, 262 green apps were counted and then analysed. What emerged from it, is that this kind of applications represent mostly feedback systems providing sustainability-related information such as energy consumption and transportation.
Green apps cover a lot of fields: food, transportation, lifestyle, waste and so on. The most frequent domain related to environmental sustainability resulted in being the mobility sector. App belonging to this area are usually concerned with offering service for sustainable mobility alternatives such as biking or car sharing. Some of them are instead related to the eco-driving concept, which allows to consume less fuel and so to reduce the gas emission by giving feedbacks to the

users about their driving behaviour. It aims at giving tips such as the correct moment to change gear during acceleration, efficient average speed depending on the vehicle and so on [11].

After mobility comes energy management. Nowadays a lot of digital solutions exist for encouraging the reduction of the energy consumption. Most of them are energy monitoring systems using some hardware, such as special plugs or sensors to attach to the fuse box. An example of mobile app using this system is PowerPedia app [12]. It's a mobile app developed by the Institute of Pervasive Computing in Zurich in 2012. As the name suggests, it's a 'Wikipedia', that is an encyclopedia, for electrical appliances. In particular this service aims to make people aware about how much their electrical devices consume and allow them to compare that consumption with that of others. The detection of the appliance and its consumption measure are taken by connecting a mobile phone directly to a smart electricity meter. Then the app displays the appliance-specific energy usage helping in this way users to understand their electricity consumption and therefore to save energy.
Similar to this last service, is the app 'Green Outlet' which detects the most consuming appliance and warn the user if it is exceeding the recommended carbon usage.

Some energy-related apps instead deal with computing the electrical bill. The interesting aspect of this kind of task is that some of them are not computing it in an empirical way, that is by measuring the effective consumption, but they return an estimated expense by solving some mathematical equations. An example of app exploiting the math is the 'Energy Cost Calculator' app.

Regarding the estimation of the electrical costs, thanks to the advent of the artificial intelligence, in the last decades companies have been starting to adopt intelligent algorithms to forecast the energy expenses. For instance, 'Neuro' app strives to predict the total cost of monthly bill by running some machine learning algorithm.

Other features, which are widely exploited, are showing the consumer's energy history and offering a comparison tool to compare their consumption with the average trend. Also, statistics about the consumption is usually provided to get insight into future costs.
All this gives homeowners the ability to reduce or shift energy use during peak times.
Moreover, all this data is usually shown by a graph over a period of time, which can be daily, monthly, weekly or other periods. This setting is often customizable by the visitors.

To take complete control over one's energy consumption, some companies developed some home automation service, which let users to set up the temperature of their home or switch off the lights while they are out. The eco-friendly idea behind it is to give the opportunity to the users to manage electrical devices to set them up remotely in order to reduce any waste of energy. An example of an app implementing such service is the 'Nest Mobile' app.

Focusing on the architecture, some apps are offering a real time monitoring service, such as 'Smappee' app. In particular, this method is adopted from those services which exploit sensors to gather energy information. After the data are collected, they are sent to the user's mobile phone to be displayed.

We can conclude from what has been presented in this chapter that nowadays most of the existing green apps are based on keeping track of energy usage in order to monitor consumption and expenses.

Chapter 4

Machine Learning and Data Analysis

4.1 Time series study

Regarding forecasting whether it is weather forecast, stock market forecast or even for ticket planes prices, the common way to do it is to consider two main approaches : a statistical approach based on mathematical formulas and a more recent one based on machine learning. In order to conduct properly those forecasts, it is necessary to evaluate the data we set as input, build a proper model and finally evaluate its performances.

The first step of this process is thus finding a proper dataset. As the aim of the project is to isolate the consumption of energy for citizens of a same area, the smaller it is the better, we look for a dataset regrouping regions. Those data for each city or each region of a country is complicated to find. To be able to test the model we will then develop with data having the same properties, even if their value will not be relevant for a common user. We therefore chose a dataset that gathers energy production of many different states of the United-States (we do not make the difference between energy produced and consumed). This allowed us to work with a series of value regarding energy production and whose values are depending on time. This is called a 'time series'. However these values reflect the consumption of several states of the U.S. and not the one of a single home. The evolution of this time series, on the contrary, mimics users habits which is the most important factor for this project. We will then focus on the evolution aspect of it.

The objective is to experiment with realistic values but intrinsically unusable for a user. This is for establishing models that can be used with the adequate data.

4.2 Import of the time series

The data come from the website named 'Kaggle', where many different datasets are regrouped. The dataset we used is a gathering of several major areas that produces electricity within the United-States and that are run by different organisations.
The dataset sums up the energy production of the states of : Texas, Ohio, Tennessee, West Virginia, Indiana, Michigan, Kentucky, Oklahoma, Arkansas and Louisiana [13]. What one should keep in mind is that we don't look for the source of the energy produced within these data.

4.3 Description

In order to establish that the dataset is what we're looking for and with the properties we need allowing us to create a proper model out of it, it is necessary to conduct some visualizations to describe it.
What we notice at first is that it is made of 121 273 lines and 2 columns that contains no missing hourly values:

- 1 line correspond to 1 hour, since 01/10/2004 to 08/03/2018.
- The first column is the date and the second column is the production in Megawatt.

We had to suppress some parts of the dataset because it was incomplete for instance the year 2004 and 2018 are only halfway represented. This data erasure didn't change much to the dataset statistical properties: "Mean", "Max", and so on. It is important that the core of the dataset stays the same even after this data erasure. 'AEP_MW' stands for the energy production.

	AEP_MW
count	121273.000000
mean	15499.513717
std	2591.399065
min	9581.000000
25%	13630.000000
50%	15310.000000
75%	17200.000000
max	25695.000000

Figure 3 : Allocation of values for the unmodified dataset

Deleting of the **2004** and **2018** years because they are incomplete.

count	113931.000000
mean	15515.180996
std	2602.462408
min	9581.000000
25%	13636.500000
50%	15323.000000
75%	17233.000000
max	25695.000000

Figure 4 : Allocation of values for the modified dataset

It is easy to highlight that the precedent properties stay of the same order of magnitude which means that the dataset is not amputated by a massive amount of data and can be exploited.

To understand it in a bit more detailed way we check its distribution of values.

What would make sense is a Gaussian distribution with a minimum value of electricity produced, a mean value around which most of the values are and a max one.
As we can see most of the values are focused around 15000 Megawatt whereas less of them are located around 25000 Megawatt or 5000 Megawatt.

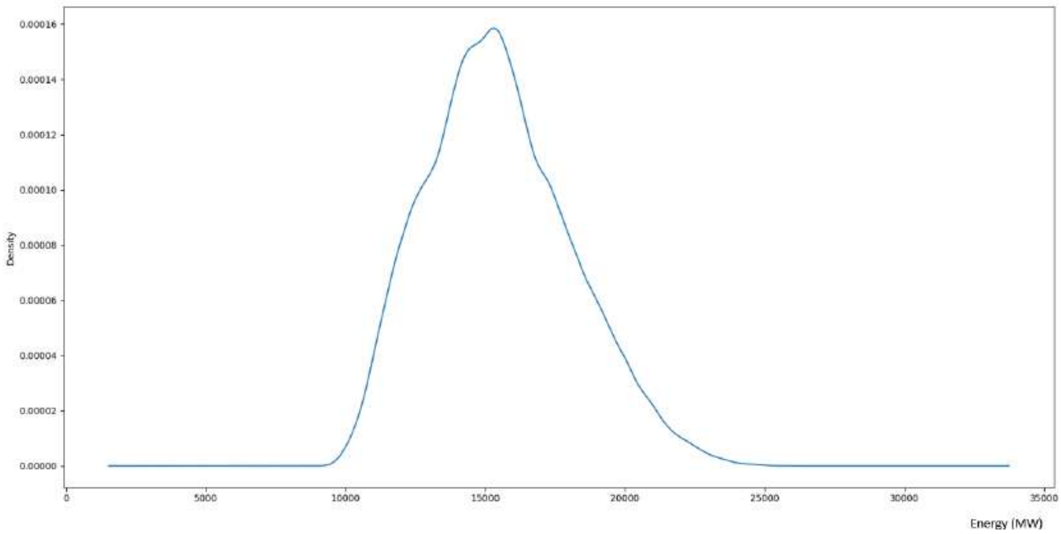

Figure 4.1: Histogram of the energy production

Now that we've understood the core of our data we need to reduce the scale to focus on specific periods of time to make sure there is no absurd values and that they are all exploitable.
To visualize that we compare years and months with each other to fully understand the dataset. If a year or months comes out as being very specific in their own way it would be thus possible to target the problem, if there is any, when the model produces its outcomes. Indeed the model we are about to go through are very sensitive to the data and can be easily biased if some of them show an important part of irregularity. This is why this investigation is necessary, to prevent this malfunction.

That's why this part of the machine learning job is so important. Knowing your data can avoid you problems with the finite model.

The share of values along years and month allows us to come out with remarks:

- Each year is similar to the previous one if we take into account the scale of values.
- The winter and summer months are highly demanding. This is probably caused by a high demand in cooling and heating during those period of times.

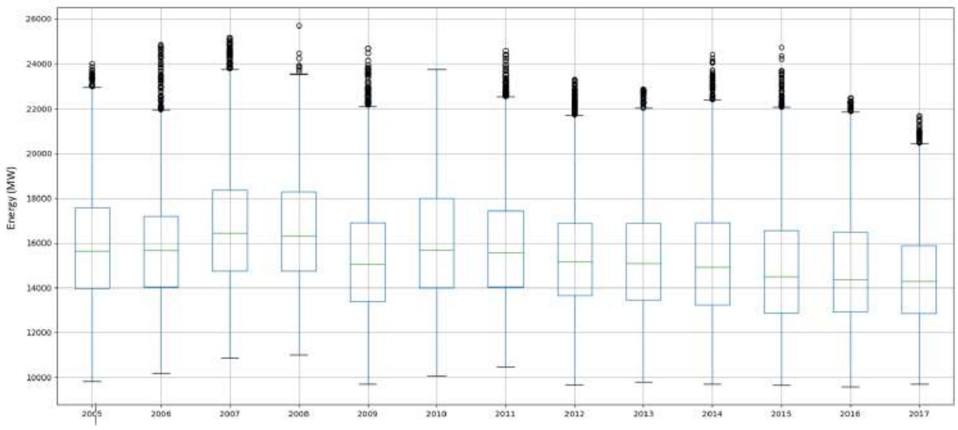

Figure 4.2: Boxplot of the annual share of electricity production

The description makes sense and matches with what we could expect from this type of data.

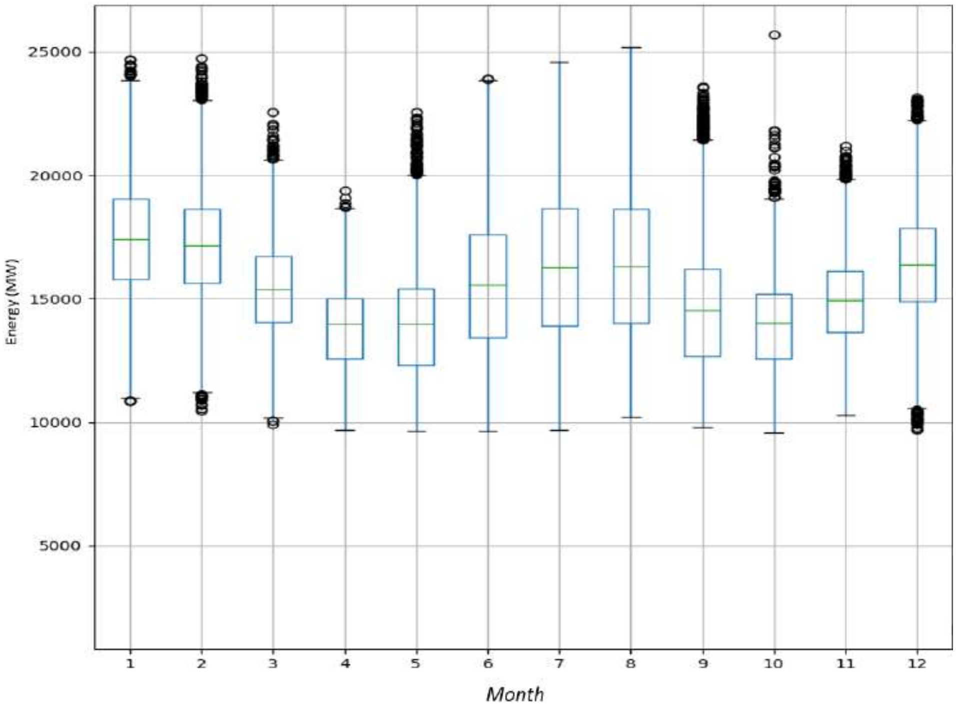

Figure 4.3: Boxplot of the monthly share of electricity production

4.4 In depth visualization

To help us understand a bit more this time series, it is necessary to look at different scales to understand the seasonality, the trend or what is called the "noise" which is made of incongruous values (outliers). Those characteristics will be helpful in case the model comes out with unsatisfactory outcome, then we could isolate the cause. Indeed, seasonality or trend is what make the data not random. It has a pattern and can therefore be predicted. However if the noise for instance is too important then it would be hard to predict anything given the fact that the data are mainly due to randomness. This is why this in depth analysis must be conducted. To make sure those kind of characteristics does not appear.

4.4.1 Yearly scale

It is easy to see a pattern when one compares the recent years (and the ongoing 2018 year).
We understand here that the time series is not random at this scale. It includes an annual seasonality.
No particular trend is observed, however the notion of noise is well shown. This means that we could face random values at some point of the prediction. We should then, not be surprised by a lack of accuracy if we have nothing to detect that a value predicted corresponds to an outlier.

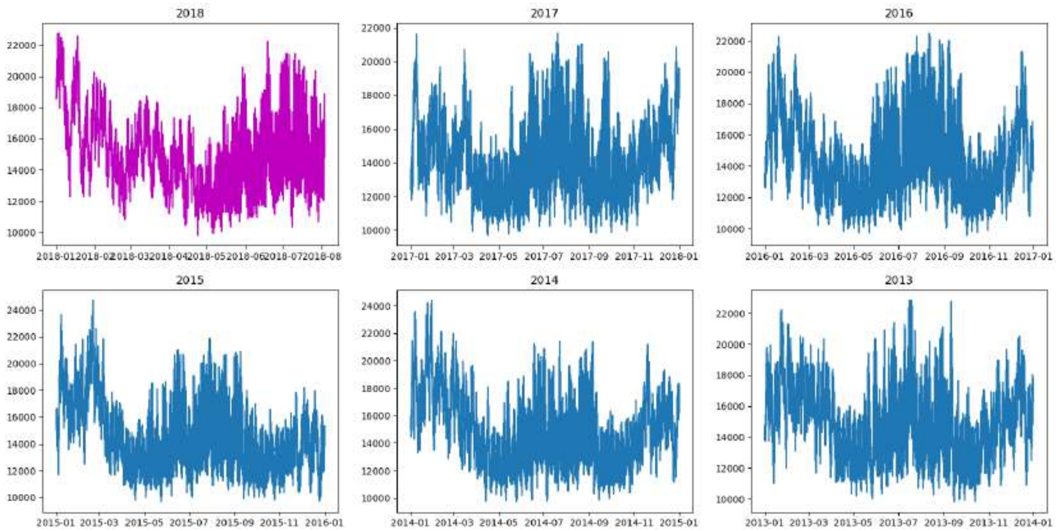

Figure 4.4: Yearly energy production from 2013 to 2018 (by hour)

As we can see the years adopt the same pattern it is therefore reasonable to continue with a random but preferably recent year to analyze the time series at lower scales.

4.4.2 Monthly scale

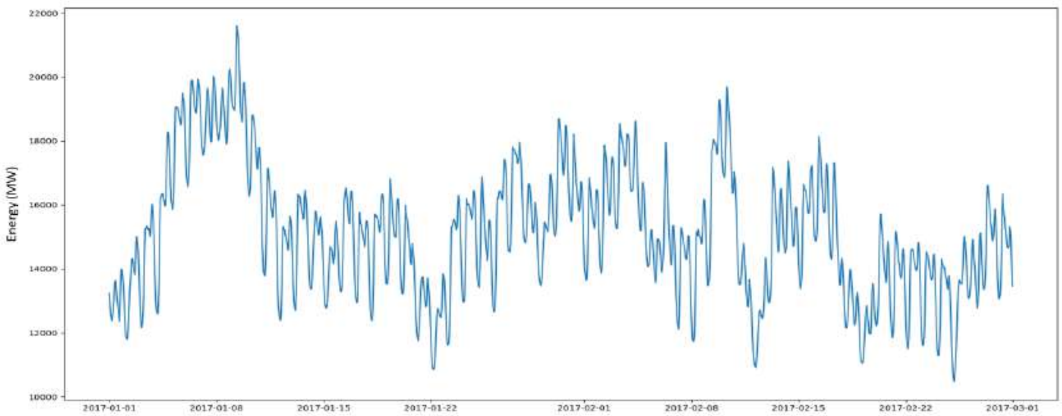

Figure 4.5: Energy production on the first 2 months of 2017 (by hour)

4.4.3 Weekly scale

We notice more precisely some sort of seasonality. It is easy to deduce that it corresponds to the evolution of a day : peaks of production are around 18h whereas production hollows are in the middle of the day or the night.
We are making progress to understand more and more our data.

All these observations agree with the experience one can have from energy production. It is high when a lot of people are coming back to their house in the evening and low when they are sleeping or at work.

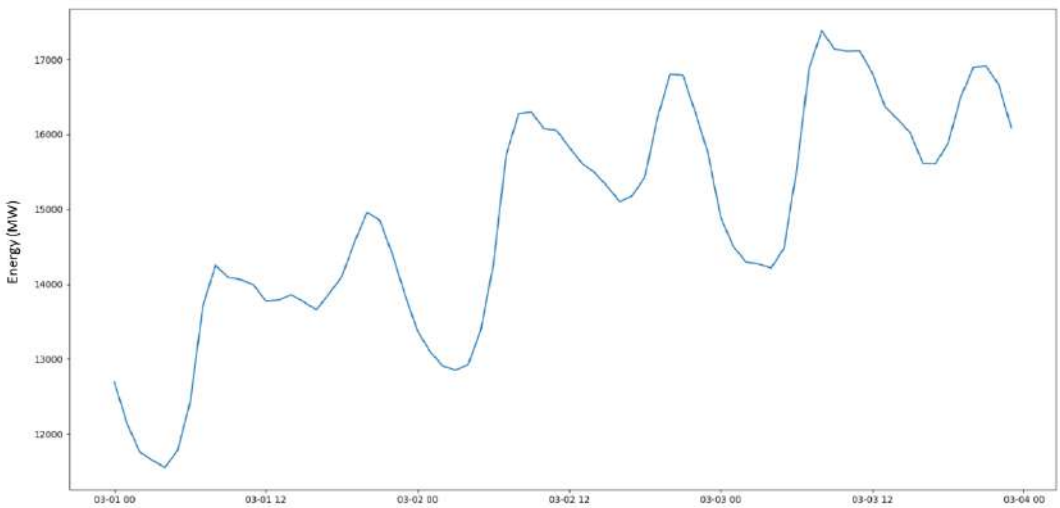

Figure 4.6: Energy production on the first 3 days of march 2017 (by hour)

4.5 Prerequisite

Now that we fully understand our data cannot be surprised by it, it is time to develop the models.
The objective of the service is to forecast the evolution of energy production depending on users needs. Therefore, it is necessary to be able to predict with a relatively high precision to highlight the activity in the coming days.
In order to do this we will use a statistical model and a neural network model to compare the two models and choose the most efficient one depending on the results as well as the deployement dificulties that we have to take into account.

4.5.1 Model ARIMA

The python library mainly used here is « Statsmodels ».

The 'ARIMA' model is short for « Autoregressive Integrated Moving Average » [14]. To use and apply this model it is needed to check if the time series is stationary: the statistical properties of the times series doesn't depend on time. If it's not the case, the time series becomes unpredictable for the method.

Note: For the rest of the project we use the differentiated time series. We simply study the evolution of the energy production by subtracting a value to the precedent one. This allows us to notice if there is an increase or a decrease.

Comparison of means and variances

The Gaussian property of the data allows us to separate the data in half and to compare the means and variances for each part. If they are of the same order of magnitude then there is no evolution of the statistical properties of the time series through time : it is stationary.

Part 1	Part 2
Mean = -0.003	Mean = 0.108
Variance = 347203	Variance =296076

Because the means and the variances are about the same order of magnitude, we can conclude that they do not depend on time : the time series is stationary. Good news the data can be used for our model.

Configuration

Another main aspects that needs to be checked for the sake of our model is how is a value at time 't' related to a value at time 't+x'. we call this 'Lag x'. The idea behind this is to understand which value in (time 't') can have a major impact on the value at another point in time (time 't+x'). For instance if it dramatically decreases then the other value will react accordingly. According to this chart we can conclude that the value at time 't' is highly correlated to the value at time 't+1'. This can be said by noticing that there is a linear function

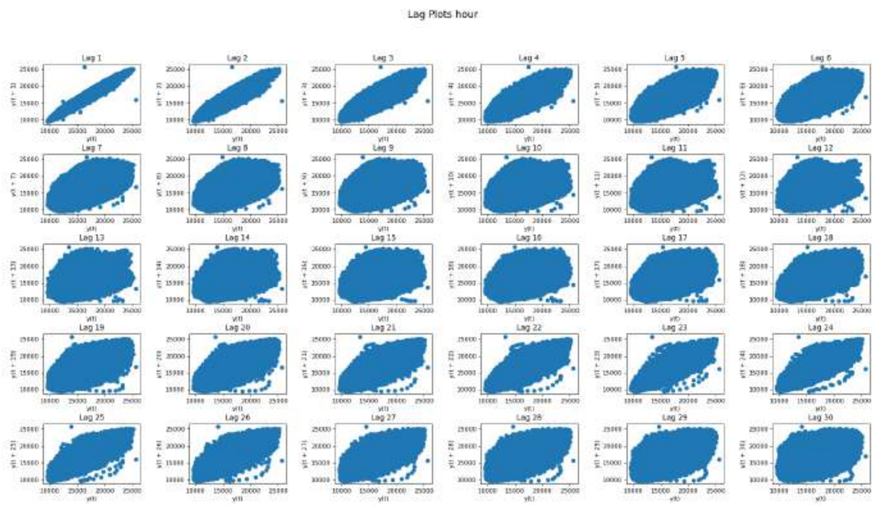

Figure 4.7: Autocorrelation between the value x(t) et x(t+N)

that can describe the relationship ('Lag 1') between those two values. What can be understood from this chart is that a value is highly correlated with the ones closer to it (the previous hour or the hour before that) or even the value of exactly a day ago : 'Lag 24'.
This observation reflects the idea that at 5pm on Monday the electricity consumption would be approximately the same as at 5pm on Tuesday.

Result of prediction

After training on the year 2015-2016 and testing on the first 72 hours of 2017 (time period that has an interest to forecast for the user because it's not too far away in time and not immediate either) we get the following results:

You can see negative values because we chose the serie where we subtracted the precedent value to highlight the evolution. One can notice that the prediction matches almost the test samples with a delay. The results seem encouraging with a prediction curve that follows the ground truth.

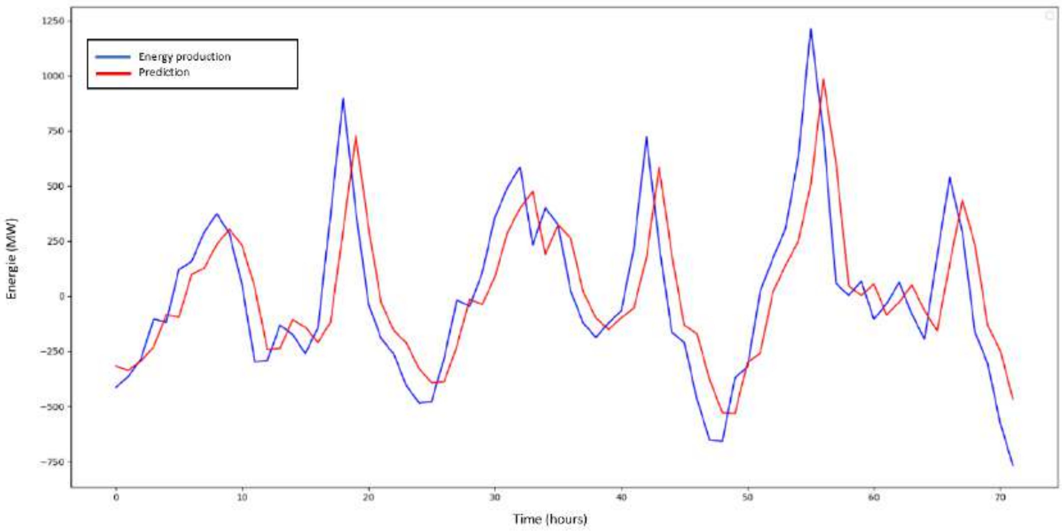

Figure 4.8: Prediction of the energy production over 72h compared to the ground truth for ARIMA (by hour)

4.5.2 LSTM Network (Neural network)

The python library mainly used here is : 'Keras'.

Type of neurons

After analysis of the different neural networks that exists with different type of neurons (SimpleRNN, DeepRNN, GRU and so on), it is best to chose the model that historically outperforms the others : “Long Short Term Memory”. This type of neuron and neural network around it has the ability to store previous information (history) in order to make a more accurate prediction. It is part of the neural networks that we call “Recurrent Neural Network”.

Construction of the network

Based on series of testing that you can check in the appendix, this network is made of two hidden layer of 'LSTM' neurons and one output layer to establish the value to predict.

After evaluating and testing the different parameters available we selected the ones as follows:

- 2 Layers;
- 60 LSTM neurones for each one;
- Activation 'hyperbolic tangent';
- Optimizer 'Adam' with a learning rate of '0.001';
- Loss function : 'Mean squared error'.

The reason behind this choice is presented in the appendix.

Results of prediction

After training on the year 2015-2016 and testing on the first 72 hours of 2017 (time period that has an interest to forecast for the user because it's not too far away in time and not immediate either) we get the results illustrated in the image 4.9.

You can see negative values because we chose the series where we subtracted the precedent value to highlight the evolution. The results seem encouraging with a prediction curve that follows the ground truth.

Once the model has been created, it is mandatory to evaluate their performances to choose between the best models.

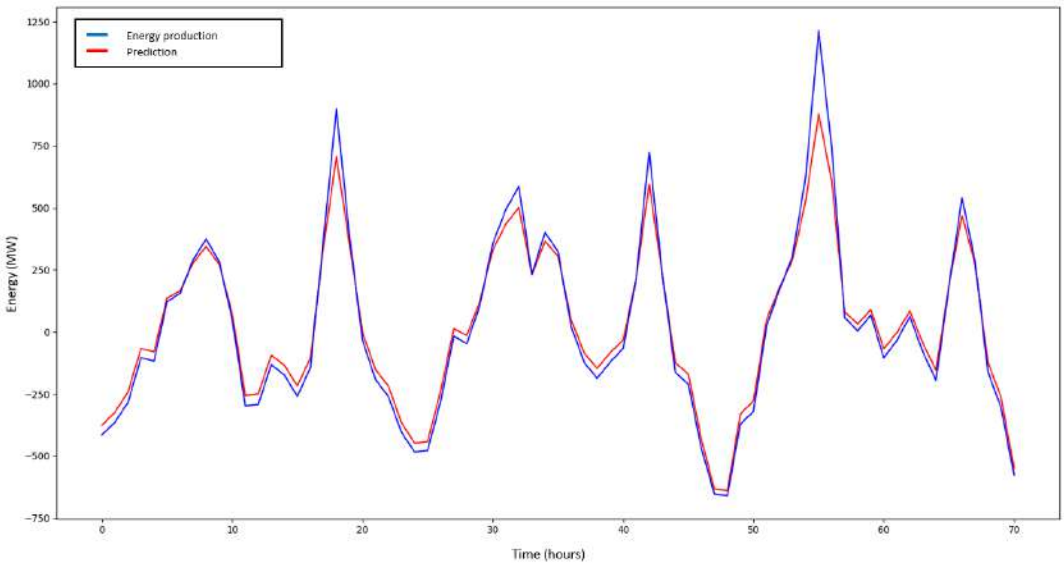

Figure 4.9: Prediction of the energy production over 72h compared to the ground truth for 'LSTM' (by hour)

4.5.3 Evaluation of performances

The tests have been conducted over the same period of time for the two models: the 72 first hours of 2017. To evaluate the performances we measure the differences between the outcome and the expected values. The smaller the difference is, the more accurate the model will be. We call this the "Loss".
We measure the average of the squares of the errors ; that is, the average squared difference between the estimated values and the actual value, the lower it is, the better the predictions are:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^*)^2$$

Loss

We can conclude from the table below that the 'LSTM' model shows a lower 'RMSE' (Root Mean Squared Error) than 'ARIMA'. It is therefore more efficient.

	ARIMA	LSTM
« **Mean squared error** »	60883	3851
« **Root Mean squared error** »	246	62

Figure 4.10: Results of the loss for the models (rounded).

The Root Mean Squared Error ('RMSE') is important to evaluate the system's accuracy and is being used to constantly test the model.

Time of execution

If the service is supposed to be developed with the help of GPUs, the 'LSTM' model is 100 times quicker to run than the 'ARIMA' one, it is therefore more likely to be the most adequate model on a real deployment.

Model	**GPU**	**CPU**
ARIMA	475	670
LSTM	5	7

Figure 4.11: Time of execution of the different models (rounded in seconds)

Now it remains only to show the next time slots where the production is at its lowest over the next 3 days (Figure 4.12).
The algorithm is then able to highlight the next time slots where the energy is at its lowest. These results will then be presented to the user.
The models could present different results for significant longer period of time to forecast. However this search hasn't been conducted.

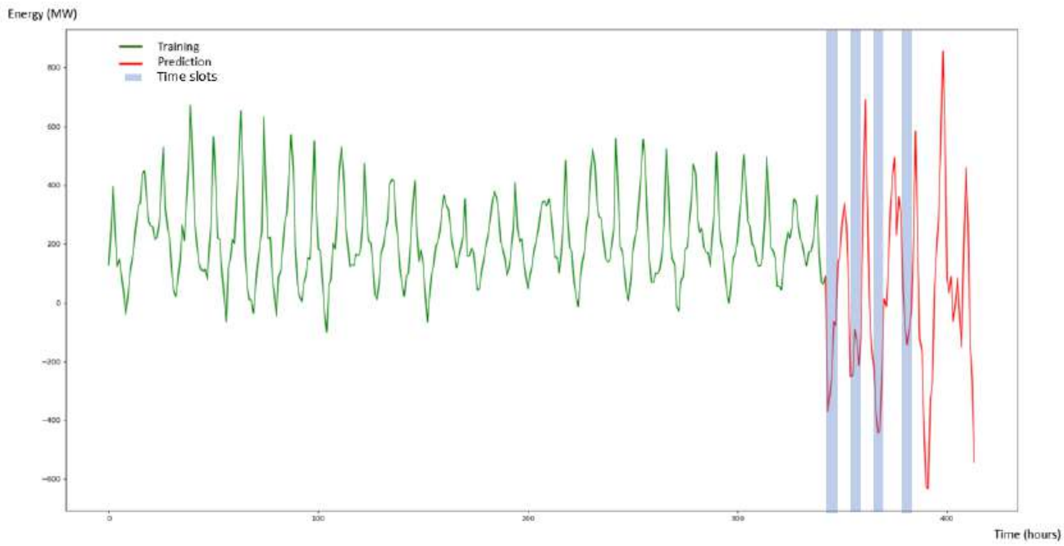

Figure 4.12: Time slots predicted within the next 72 hours

The machine learning part being done we now need to present the results in the most adequate way to make it understandable by the users. That's the objective of UI and UX design.

Chapter 5

UI and UX design

In this chapter we are going to present the interface of the 'ManEl' app we prototyped. For prototyping our app interface, we took inspiration from existing apps, without overlooking the UI guidelines. In this presentation, we highlight the set of UX and UI mobile design principles and patterns we took into account as well as the psychological effects we took advantage of to display the machine learning results the best way.
We designed two interfaces, where the latter was mainly brought to life after we got feedbacks from a first user involvement.

5.1 General style

In the first part we present our work by discussing the general style we adopted for both of the interfaces.

We looked at the Apple's design style, which choice was taken arbitrarily to get a first inspiration. We also tried to keep the style as modern as we could by adopting first the minimalist design principle [15] and Hick's law [16].

The minimalist design is the most applied practice in the digital products of nowadays. It focuses on using clear forms such as lines and whitespaces in order to make the design concise, clear and consistent. Hick's law on the other hand states to use the less number of options as possible to simplify the cognitive load and so to reduce the time users take to make a decision.

For arranging the components, we applied the Gestalt laws [17]. They are a set of heuristic psychological laws, which describe how we perceive the world. Their exploitation allowed us to make our interface be perceived in a more pleasant way, such as aligning all items in a symmetric way.

Regarding the background and colours, for both of the wireframes we chose a countryside landscape as the home-page background to remind the user the concept of sustainability. This is emphasized by the sentence we wrote above the input form: 'For a healthy world, manage your energy consumption'.
The background was also chosen by taking into account the meaning of the colours [18]. Indeed, as it's possible to notice by looking at the screenshots (such as in Figure 5.17), the main colours our background is made of are blue and green, which give the users a calm feeling. We maintained the same expression in all the screens by blurring the background.

5.2 Functionalities and interactions elements

In this paragraph we are giving an overview of the interactive components we implemented in the final version of our application. Some of them are also present in the first draft of our interface. Here we overlook the design and technical aspects, which are being discussed in the following chapters.

Both the apps consist of a text box (Figure 5.1), whereby the users are required

to input a Danish location, which has to be the name of a city. This location was chosen to simplify the project and to agree with our university location. This represents the only input form users have to fill in. Moreover, as it will be discussed in the chapter 5.5, here we built some features: the **predictive text** and the **auto-localization** option.
Regarding the error management when a wrong city is inserted, we chose not to give any errors. When the city typed is not existing in Denmark, because either it's not a Danish one or its spelling is wrong, there will not be any predicted text and the 'view' button (visible in figure 5.16) will be disabled. This is a wide used error management system.
When it comes to ambiguities, which is the case when there exists cities with the same name, we checked that there are no homographic Danish towns. [19].

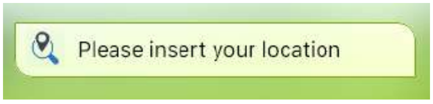

Figure 5.1: Text box to input the Danish location.

An app menu has also been built in and it's accessible by tapping on the well-known hamburger icon menu placed on the top left corner (Figure 5.2).

Figure 5.2: Tappable hamburger menu icon

An icon for enlarging the graphs is present and also one to shrink it appears on it as the graph becomes larger (Figure 5.3).
User can also zoom in and out the graph by just pinching on it.

Users can easily navigate in the app using the navigation menu (Figure 5.4), which allows them to change the period of time for the forecast. Users can

Figure 5.3: Tappable icon to shrink (the former) and enlarge (the latter) the graph

choose the prediction of energy consumption for the city already selected among day, week or month.

Figure 5.4: Navigation menu

On the chart it is displayed as many blue rectangles as the number of time slots computed. These forms can be selected when a user taps on it to see information about the related time slots. These information will be displayed on the static text box on the top of the interface. In particular it is shown the start and end of the time slot.
The container containing the time slot information is swipeable (Figure 5.5). This means user can slide their finger to see a different time slot.
Summing up what have been said so far, to look into the time slot, user can either swipe toward left or right the 'time slot container' or tap on one of the blue rectangles shown on the graph.

Figure 5.5: Swipeable container during a swiping animation.

A tool to look into every value of the graph has been implemented (Figure 5.6). User just needs to slide it left or right to see the exact amount of energy production and the related time it was or it will be generated (the graph reports both the history of the production and the forecast of it).

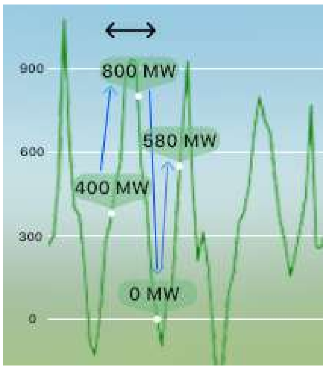

Figure 5.6: Example of the magnification tool. Sliding in to left or right, user can see in detail the value of the curve in a specific point.

A bell icon is present in the time slot page to allow users to enable/disable notifications related to the city they looked into. The working principle of this notification system is explaining in the chapter 5.5.

5.3 First interface prototype

As the app is launched, the first screen to be displayed comprises the logo of the app (figure 5.7). This screen is intended to be the welcome screen, which is technically called 'Boot screen' or more 'Splash screen' [20]. It is considered as a source for brand strengthening and start out the app loading process. Moreover, the splash screen creates a first perception about the application and as an old saying goes "First Impression Lasts".

After the welcome screen, the user is redirected to the 'Home page'. Here, the

visitors can insert the location, where to look into for the consumption. We minimized data input and made it simple by not including a sign-in process. This let us reduce the cognitive load since users are not required to remember any credentials to log in.
Through this page, user have also the possibility to access the hamburger menu by tapping on the icon placed on the top-left corner. From the menu-page, users can report problems, manage their notifications and look into how to use the app if they have some doubts about that.

Once the user input the location, they are redirected to the time-slot page. Here we established gestures. Indeed, we included the possibility to scroll the graphs sideways.

The 'thumb zone' practice was also taken into account in all the pages. In thumb zone we mean the area of a phone's screen that can be easily accessed with the thumb when a person is holding their phone with one hand [21]. This guideline consists in putting the majority of interactive content in this zone.
As it's visible from figure 5.7, we put in the 'thumb zone' the graphs so that the users can use just their thumb to navigate into the chart. An option to enlarge the chart is also available. This feature can be activated in a quick way by just turning the orientation of the phone into landscape (visible in the last screen in figure 5.17). We also considered adding a manual system in case the phone can't be set in a landscape view.

Looking at the bottom of the time-slot page, we can admire the navigation menu. It was designed by taking into account the Gestalt law (as mentioned earlier) and by adopting well-known and intuitive icons. In designing it, we also implemented the serial position effect to assure a good user experience [22]. This psychological phenomenon describes the people's habit to remember the first and last elements of a list. For this reason, we set the 'Home' icon as first shortcut of the menu for the home page.

Figure 5.7: Sorted-work flow first prototype

5.4 User Involvement and feedbacks

After developing our interface, we printed it in order to get a paper prototype to use to test our design. For this reason, we interviewed four potential users. The interview was taken in a friendly way starting from a normal conversation about their general knowledge regarding electricity consumption and how it affects the environment. Soon after, they were presented with the prototype to get some feedbacks.

After that we presented the wireframe to our first participant, it took her a few minutes to figure out what the app was about. At the first sight, she thought the aim of the app was to predict the price of what people consumed. Later, when she was assigned three basic tasks (enter a location,point out the lowest consumption time slot to come, set a reminder on her own calendar), she understood the idea behind the app. As she was familiar with other prediction apps such as weather forecast, she was able to complete the tasks in a short amount of time.

When she was asked to give feedback, she mentioned that in her home country (Asia), this app would be meaningful. However, she doesn't personally bother to track her consumption rates and bills. Besides, she was aware how much pollution power plants generate.
Regarding the style, she appreciated the choice of the colours. She also stated a notification feature should be added to notify possible reduction in the bills if consumption rate is low.

The second user admitted she has little knowledge about electricity: she never looked into how the price of the electricity is decided and the effects its production bring to the climate.
Later, when she was handed the prototype to perform the task. When she came to the graph she was expecting to see also the values of the consumption rate. She appreciated the aim for which the app was designed and also the colours used. Moreover, she mentioned that the app could have more meaning in her home country where the price of electricity is really expensive in comparison to Denmark.
In her opinion, the main drawback is to match her organisation of the day depending on the day when the consumption will be the lowest. An interesting topic she pointed out was how she can manage the electricity if the consumption rate is low during the night.

The third participant knows how the electricity is generated from both renewable and non-renewable resources. He was also aware about the variable prices of electricity depending on the demand, source of generation and availability of power plants.
According to him, such apps can be worthy for both individuals and organisations where one can have control on the way of consuming electricity. He also

added the information about energy consumption can help the government and other parties to make suitable investment plans.
He also suggested adding a feature which allows user to pay their bills directly from the app.
Regarding the interface, he suggested making the graph more clear, but appreciated the overall design.

The fourth user had no idea about electricity prices but she had some basic ideas about the sources of electricity. Moreover, she believes in sustainability and thus she was aware of the importance of using as little power as possible and the importance of exploiting renewable sources.
As she was given the prototype, she thought the app was an electricity price calculator. After we explained to her the idea behind the app, she said her mother could be one of the users: her mother uses basic and manual solutions to consume less electricity.
She appreciated the reason for which the app is going to be developed. Her suggestion was to add a user login page to let users create their profile for tracking their consumption habit and make comparison between specific time periods.

Summing up, most of the interviewed people found the graph a bit unclear and suggested adding some extra features (notification system, user profile and bills payment).

5.4.1 Summary of the user involvement

1. Most of the users did not know about the factors that price of electricity can depend on time.

2. Apart from one, three of them performed the task without difficulty.

3. Most of them appreciated the design and motive behind the app.

4. They commented that this app could be useful for both residential and organization uses.

5. Most of them have difficulty to understand the graph and suggested to make the consumption values appear on it.

6. One of them suggested a user profile on the app to see how the electricity has been consumed.

7. One of them suggested to use some indication icon to show the forecasted highest consumption time slots too.

5.5 Second interface prototype

After collecting all the responses from the interview, we took their feedbacks to improve our interface and come up with a new version of it. In this work we mainly focused on making the graph more clear and the overall style more pleasant. Regarding the features which were mentioned we decided to implement only the notification system. The user profile and bill payment were neglected in this project in order to keep reasonable the work load, but they could be an idea for a future development of the app.

Starting from the design, based on the decision mentioned in the first interface about using an Apple design style, in this second version we adopted the font Apple uses for its mobile devices.

The permissions in-context were also added (Figure 5.8). At the first use, the app informs the user through two system dialogues that the app itself is going to use their location and send them notifications. If the users deny them by accident or on purpose, they can be activated later by the menu app (Figure 5.11).

Moreover, we designed an on boarding experience by adopting the Nickel Tour principle [23], which consists in guiding the user through their first use of the app showing them the fundamental features by some screens (Figure 5.9).

In figure 5.17 is showed a sorted-flow about how the app would look like for a first-use.

Figure 5.8: System dialogues for using auto-location and sending notifications.

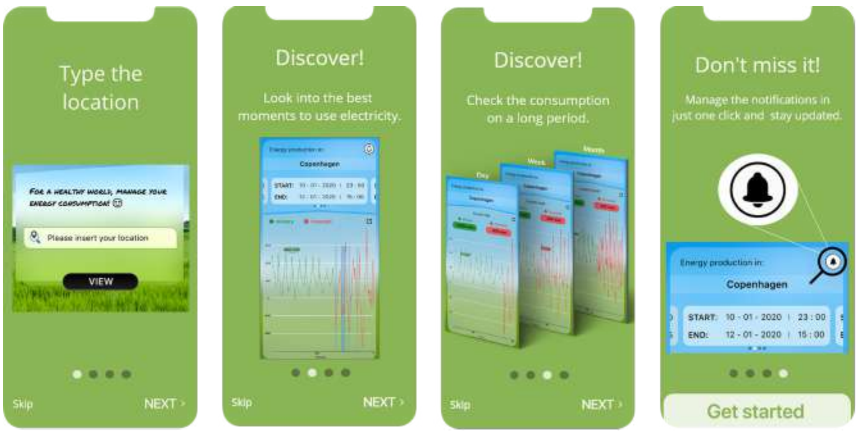

Figure 5.9: Sorted-flow about the on boarding process

Coming now to the Home page, we exploited the 'recognition rather than recall' concept [24] by adopting the built-in iOS search engine (Figure 5.10 a). This concept gives users clues about what to type in order to reduce the mental load. Furthermore, since it's supposed user insert a location which might be the city where they are currently using the app, we added the auto-located option to speed up the input process (Figure 5.10 b). This feature could easily be implemented using an open source geolocation API available online, such as the one developed by Google [25]. However, we let users the chance whether to use it or to enter the location manually. In particular, in our implementation the auto-location option is shown only when the user doesn't type anything and disappear as soon as a character is typed. To make that feature appear again, users only need to delete what they wrote.

(a) iOS search engine **(b)** Auto-location

Figure 5.10: Details about the data input Home page

Through the home-page, user has also the possibility to access the hamburger menu which has been redesigned (Figure 5.11).

As represented in the work-flow shown in figure 5.17, once the location is

Figure 5.11: Menu app ManEl

inserted, the user is redirected to the loading page. This screen is going to be displayed until the results are ready to be shown. For this reason we tried to make the waiting-time more pleasant by using a creative progress bar and by giving feedback to the user about the purpose for which they are waiting. A wind turbine was chosen as loading indicator, which could be animated by making the fans rotate and the clouds move. In this way, we can manage to keep the attention of the users on the screen (Figure 5.12).

Figure 5.12: Loading page ManEl with the progress indicator beside

Once server finishes to compute the data, the time-slot page is the first screen to be displayed. Here we established new gestures. Indeed, we included the possibility to zoom the graphs just by pinching on it. Users are allowed also to swipe to see a different time slot. Moreover, we included an apple icon, called 'page control' [4] and a visual widely-used approach to let users know they can slide it to change information. This method is based on showing just a piece of the next and previous information: in the top swipeable area showed in the figure 5.14, it's possible to see that the next piece of information is consisted of some writings starting with 'S' and 'E', while the previous one was some numbers finishing with '0' and '5'.

As it's visible in the figure 5.14, we put in the 'thumb zone' the graphs so that the users can use just their thumb to navigate into the chart, check the value of each point of the line by just sliding a dot on it and looking at the time slots. Indeed, the time slots are indicated in the chart as blue rectangles. As user tap on one of them, the information related to the selected slot is immediately displayed on the top swipeable area.
Regarding the system notification feedback gotten from the interview, in the right-top corner a bell icon was placed to enable or disable notifications in a fast way. In designing this feature, we exploited the stroke-fill strategy, which is part of the minimalist design principle. When the icon get filled, the notifications have been activated for the location which user looked into. Otherwise, if it's only stroked, the notifications are disabled (Figure 5.13).

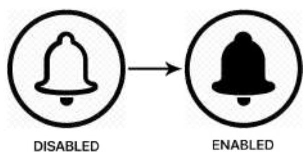

Figure 5.13: Notification icon system in Home page

Looking at the bottom of the time-slot page in the picture 5.14, we can admire the navigation menu. In the light of what has been done in the previous interface, we highlighted the navigation icon by blurring a rectangle over it. This is a heuristic guideline, which is based on getting easier for the user to know where they are while navigating the app.

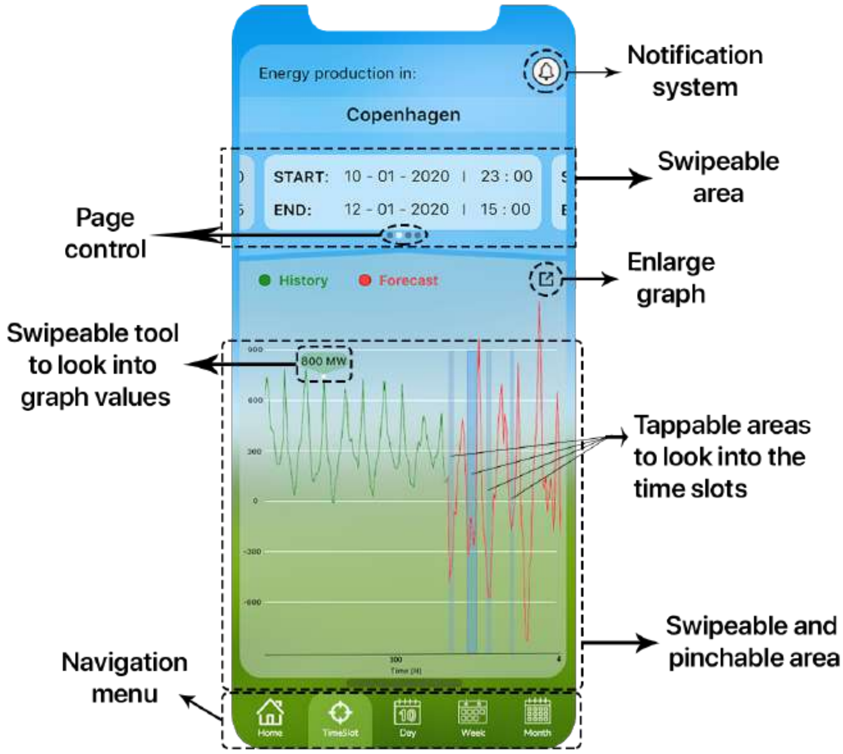

Figure 5.14: Time-slots page with highlighted features

In the event the servers can't be reached by the app or in the case where the results cannot be computed due to a too high forecast error by the algorithm, we implemented an error screen. Here we implemented a red button to allow the user to repeat the operation. For the user understanding, we kept the same image as the one displayed in the loading page but we edited it in order to express that an error has been encountered (the wind turbine now is broken)(Figure 5.15).

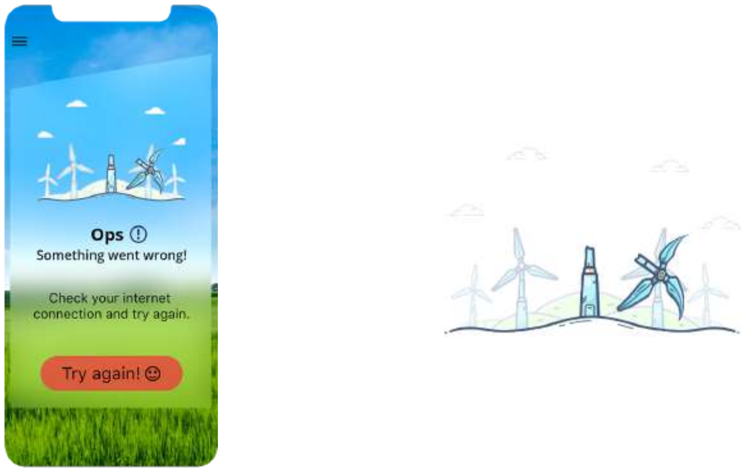

Figure 5.15: Error screen and the error image.

Figure 5.16: Sorted-flow about how the app works at a normal use

Sum-up updates introduced in the new prototypes

Here is a summary of the new features we added in designing the last prototype.

1. A tappable areas to look easily into the time slots was added.

2. The navigation bar icon is now lighting up for letting users know where they are while they navigate through the app (Serial position effect).

3. Loading page was redesigned to make it appear more creative in order to reduce the frustration about the waiting time.

4. Some icons were changed to give a better look at the interface. In particular

the enlarge/shrink icons on the graphs and the page control icon were added/changed.

5. The data are now shown more clear: the information about the time slot have been highlighted on the graph by adopting blurred rectangles. Moreover, users can now study the value of the consumption for every hour by swiping a lens tool over the graph. Furthermore, the graph was made more readable by adding white lines across it, changing the background and adding a clearer scale.

6. The on boarding screens were added since three out of four users took some time to figure out how the app worked.

7. The appearance of the menu app changed: the background colour are now blue and the lines between options were removed (Gestalt laws).

8. In accordance to the interview, an easy and fast notification system was implemented.

9. The input are now easier: the auto-location option and the iOS search engine was adopted.

10. The overall design was changed in order to try to make it appear more modern just like mobile designs of nowadays.

11. The error management in case the computation can't be carried out.

The interface being now ready and the machine learning algorithm functional, the next step is to figure out how can the system be implemented in order to make it fully functional. However due to work load constraints the next chapter will be an overview of the foundations of such implementation.

Figure 5.17: Sorted-flow about how the app works at a first-use

Chapter 6

System design

How can we implement this whole system is the reason why this chapter is made for. This section is the description of the designed structure of our 'ManEL' system.The purpose of having system design in the project is to provide information about how the system and the system elements can encompass with the implementation of the ManEL sytem.

6.1 Requirements gathering

Requirements gathering is the starting point for the system design. The functional requirements are description of services the system should provide, how the system should respond towards particular inputs and how the system should act in specific situations. On the other hand, non-functional requirements are the description of how the system should provide the service. They are system properties such as reliability, availability, performance, or security [26].

To gather the functional and non-functional requirements of ManEL, we created a user story(more information about the user story can be found on the appendix) from the open interview we had with the users. From the user story we summarized their sequential steps when interacting with the prototype of the app. Most of the requirements were discovered from those sequences of user activities while few were discovered from the second prototype of the app.

6.1.1 Functional requirements

1. The system shall display on boarding tips for the first-time use.
2. The user shall consent for notification.
3. The user shall consent for location.
4. The user shall enter his/her location manually.
5. The system shall access the user's location.
6. The system shall display the time slot graph based on location input.
7. The user shall change the time period by selecting a day.
8. The user shall change the time period by selecting a week.
9. The user shall change the time period by selecting a month.
10. The user shall swipe a lens tool over the graph to study the consumption value.
11. The user shall change the view mode into portrait either clicking on an icon placed on the corner of the graph or turning the phone.
12. The user shall enable the notification by clicking on a bell icon or setting from the menu.
13. The system shall send notification to the users about lowest consumption

time slots.

14. The system shall display a rotating fan while the users are waiting for the prediction values.
15. The system shall be able to predict the approximate low consumption time slots.
16. The system shall update the computation every hour.
17. In case the system can not reach the forecasts due to connection problems or algorithmic errors, it shall notify the users with an error message.

6.1.2 Non-functional requirements

1. Speed: The system should provide the prediction value in short amount of time.
2. The system shall compute the forecasts up to a month, every hour when the database is updated.
3. Ease of use: The system should have simple interface for users to use.
4. Reliability: every 3 days the system shall compare the previous forecast of 3 days ahead with the actual ground truth (once it is available). Then the system shall compute an error ('RMSE' as mentionned in the machine learning chapter) of less than 70 to be able to display the next forecasts on the interface : value based on the machine learning prototype results for the 'LSTM' model.

6.2 Use case

Use cases describe the interactions between users and a system [26]. They identify the actors involved in an interaction and specify the types of interaction. The use cases of ManEL are again derived from the requirements specified for the app.

The use-case model illustrates the interactions between the app, and the users, i.e. the one who browses the lowest time consumption slot of electricity based on the location they provide.

Below is the use case diagram depicting all the possible interactions in ManEL system .

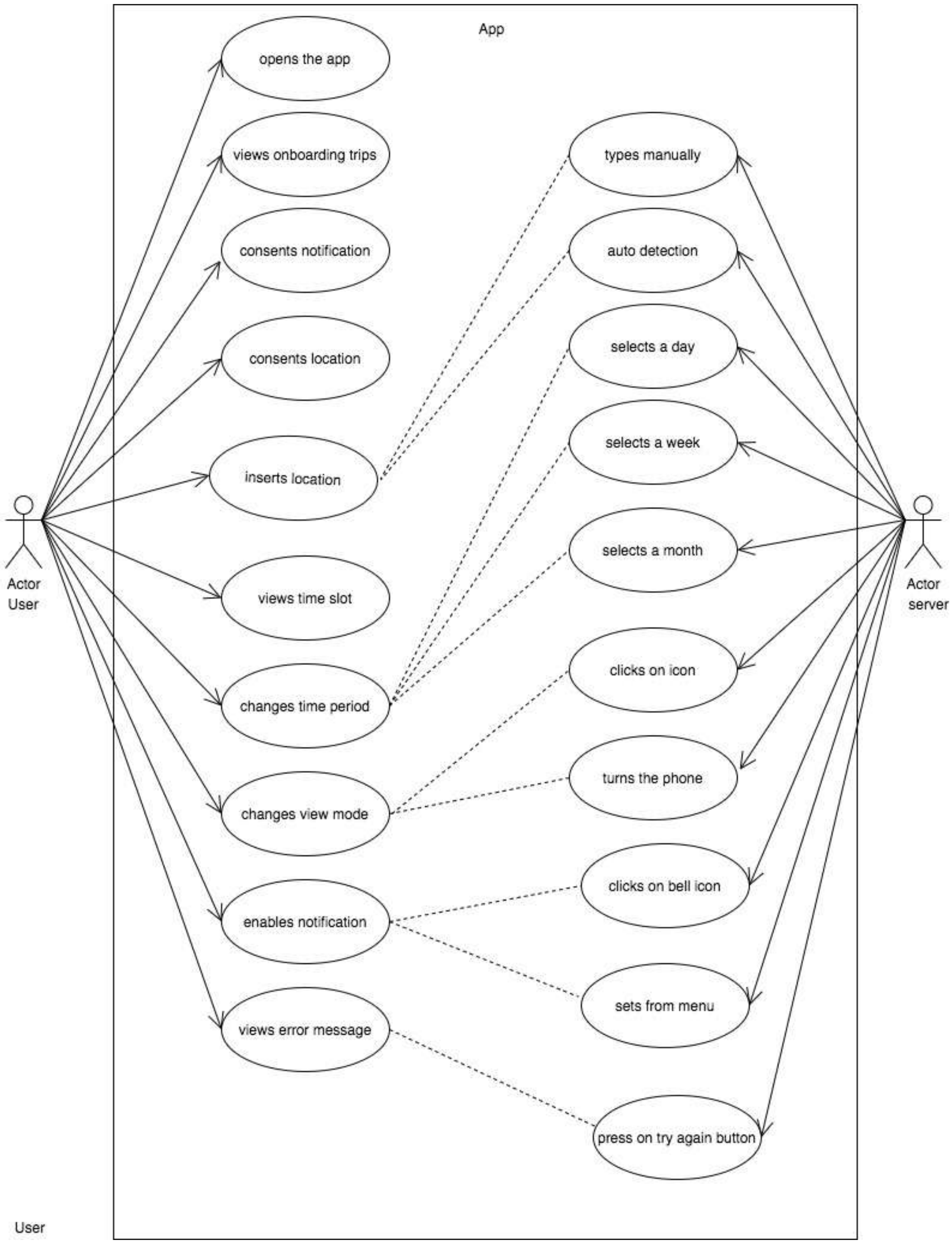

Figure 6.1: Use cases for ManEl

6.3 Actors

There are two main actors identified in the ManEL app's system:

- Residential Consumer, who want to reduce their electricity bills.
- Server, which stores the hourly calculated consumption rate.

6.4 Use case Specification

Use case 1: View the onboarding trip.	
Primary Actor:	Residential Consumer
Pre-condition:	The app is opened for the first time.
Triggers:	The app is aware it's the first time it is launched
Basic Flow	1. The app provides the user with the onboarding trip. 2. The successive page contains tips about how to use the app: entering location, viewing the time slots, changing the time periods and enabling the notification. 3. The user continues to click on the next button to move on the next page until the trip is complete. 4. As the trip finishes, the home page is displayed and therefore user can start to use the app.
Extensions	1. Alternatively, the user skips the trip by clicking the skip button.
Post Condition	1. If the user completes the trip, the user is ready to use the app. 2. If the user skips the trip, the user is still ready to use the app.

Figure 6.2: Use case 1

Use case 2: Enter the Location	
Primary Actor:	Residential Consumer
Pre-condition:	The app is opened for the first time.
Triggers:	The user clicks on the text box to enter their location.
Basic Flow	1. The system asks the user for the permission to use their current location (and right after it's asking permission to send them notification. This is discussed in use case 5). 2. The user allows the system to use their current location. 3. The user clicks on the text box where a location has to be inputted. 4. An auto-location option is immediately displayed. 5. The user clicks on that option. 6. Automatically the system detects the user's position and shows it on the box form.
Extensions	1. Alternatively, the user either ignores the auto-location option or doesn't allow the system to detect it. 2. The user types their location manually and the auto-location option disappears as the user starts to write. 3. The system suggests possible locations based on few words of the user inputs. 4. The user either selects auto-suggested location or continues to type their location. 5. To confirm the location the user has to select it on the location list shown.
Post Condition	1. If the input is valid, that is the city is Danish and it exists, it appears as a suggested location in the list even if the user writes it entirely. 2. If the input is not valid, no clues about the location are displayed.

Figure 6.3: Use case 2 example: user chooses to type the location manually

Use case 3: View the time slot graph	
Primary Actor:	Residential Consumer
Pre-condition:	A valid location is typed.
Triggers:	1. The user has clicked the **view** button and the location was correct.
Basic Flow	1. The loading page is displayed. 2. The app displayed the time-slot page which contains a graph about the predictive consumption rate for next three days.
Extensions	1. The user changes the viewing mode of the graph from portrait to landscape either by turning the phone or by clicking on the icon to enlarge the graph in a full-view mode.

Figure 6.4: Use case 3

Use case 4: Change the time period	
Primary Actor:	Residential Consumer
Pre-condition:	A time slot graph for three days is displayed.
Triggers:	The user has clicked the either **day, week** or **month** button from the menu navigation bar.
Basic Flow	1. The app shows the graph related to the time period users has selected.
Extensions	1. The user changes the viewing mode of the graph from portrait to landscape either by turning the phone or clicking on the icon to enlarge the graph.

Figure 6.5: Use case 4 where the rest of the interfaces have been omitted.

Use case 5: Enable the notification	
Primary Actor:	Residential Consumer
Pre-condition:	The app is opened for the first time.
Triggers:	The app is aware it's the first time it is launched.
Basic Flow	1. The system displayed a message to allow the app to send notifications. 2. The user clicks on **allow button** to enable notification. 3. The home page is shown.
Extensions	1. Alternatively, the user denies the notifications. 2. User click on the hamburger menu icon. 3. The user clicks on the **notification** icon to open the notification page and manage the notifications.
Post Condition	1 If the user enables notification, the users receives notification about the low consumption prediction of his/ her area. 2 If the user doesn't enable notification, the user doesn't receive notification.

Use case 6: Error encountered	
Primary Actor:	Residential Consumer
Pre-condition:	The user sends the location input to the server.
Triggers:	Something is preventing the server from sending the data to the app such as a bad connection or a forecast error.
Basic Flow	1. The system displayed an error screen to warn the user the request cannot be accomplished. 2. The user clicks on **'Try again'** button to be redirected to the home page. 3. The user can choose whether to try again or not.
Extensions	1. None
Post Condition	1. The user decides not to send again the input and try later. They thus exit from the app.

Figure 6.6: Use case 6

6.5 Context diagram

The context diagram shows the flow of information between the system and its external entities. In ManEL system, the external entities are the user and the server. The diagram below depicts the context diagram of ManEL system.

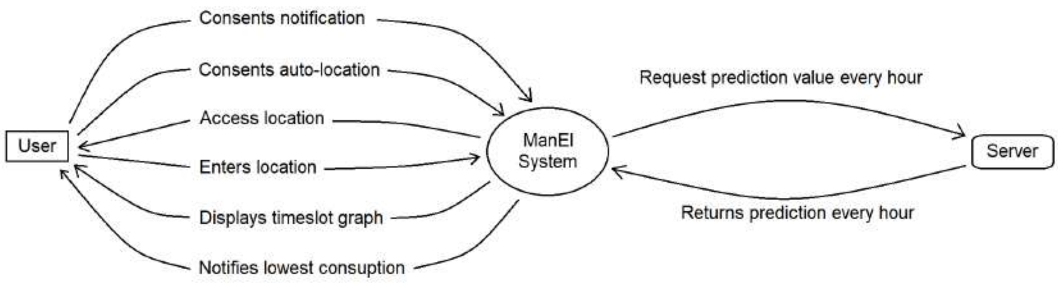

Figure 6.7: Context diagram

6.6 System Architecture

The diagram below shows the overall structure of ManEL's system. It shows the functional structure of the system presenting the sequential flow of data.

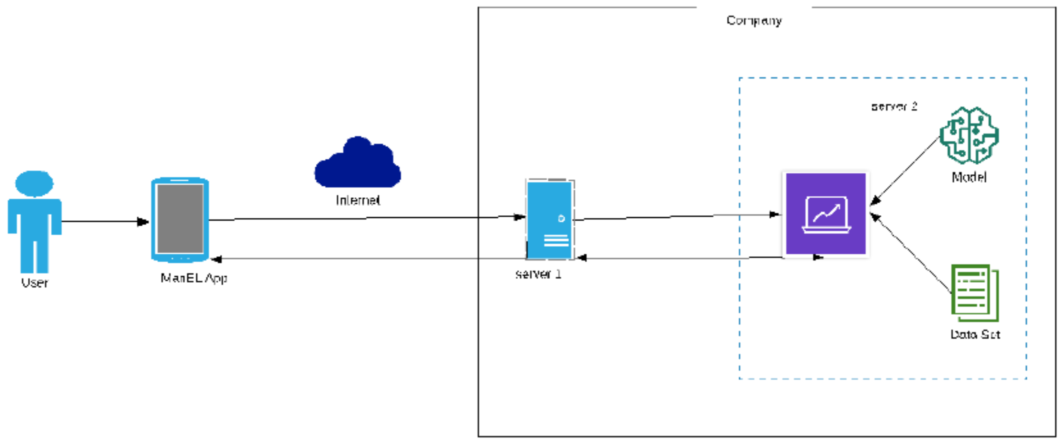

Figure 6.8: System architecture of ManEL

The above diagram represents the client-server architecture of ManEL app. After the user enters a location to see the predictive consumption time slots, the app asks server 1 for the data to show on the graph. Indeed, it contains the pre-calculated results provided by server 2.
Server 2 is dealing with the computation of the predictions by exploiting both the dataset and the machine-learning model we built. It computes the data every hour once the dataset is updated with a new value of energy. The server 1 stores the results after requesting them to server 2 every hour.
If server 2 does not provide the forecasts due to algorithmic errors or connection issues server 1 sends an error message to the app. Same goes if there is no connection between the app and server 1.

To sum up, this chapter allocates requirements of the system, identifies each components in it, illustrates interaction between each components. Overall, it suggests a system architecture.
By presenting all these activities, this chapter provides a first glance of the essential foundations needed to implement this kind of system.

Chapter 7

Discussion

We start our discussion first by focusing on the machine learning technique we adopted. Later, we move on discussing how the service provided could be improved by installing some devices.

7.1 Model selection

The LSTM model appears to be more efficient and faster to strive so it is the most suitable model. If the service is aimed at users who want information quickly, it is interesting to wonder what the implementation on actual servers would affect the processing time of the algorithm. In addition, each time the data stream has to be updated because of the last values that were entered, the model has to update itself. It is therefore necessary to redo the calculations and that might be both too time consuming and power consuming. Therefore it is a question that would require a lot of in depth analysis which we chose not to conduct due to the work load it would involved.

7.2 Reliability of the model

The reliability of the model is relatively correct. Nevertheless, one may ask whether such discrepancies (a few megawatt) could be suitable for a demanding clientele that would base its expenditure on these predictions. Predicted evolution follows the ground truth, but it cannot be determined exactly.

The system should be tested with user-wide data to understand the real impacts. In fact one could wonder that the data used for the prototype that mimics american's habits can be completely biased for an other country and therefore induce errors

In case of a major event such as a pandemic the system would rely on obsolete data which could make the whole system obsolete as well by predicting wrong values. There is no solution known compensate this phenomenon.

7.3 Future developments of the model

To strengthen the model it is necessary to add other variables such as oil, coal, gas prices or even the weather (temperature, brightness). The time serie would then become a multivariate time serie and would be able to better predict the evolution and the absurd values more accurately.It would also respond better to unexpected phenomenon such as crisis.

7.4 Requirements testing

The requirements for the ManEL system have been regrouped, but they need to be analysed, classified, specified and tested. Unfortunately, we could not do it due to work load. However, this can be done with the involvement of customers, system end users, different kinds of people within the company or even with stakeholders who have both direct and indirect influence on the requirements. Moreover, more details can be added on how the system should fulfill these requirements. Furthermore, to find out whether the requirements are met or not, the requirement testing methods such as 'black box' or 'white box' can be followed.

7.5 Service improvements

Based on recommendations from testers of the first prototype we can come up with future add-ons to make the app more useful.
For instance with the precision of the system and the installation of smart meter it would be possible to monitor its own consumption and receive real-time alerts on smartphone regarding:

- Personal consumption;
- Energy saved;
- Money saved.

It is easy to predict that this kind of service could be used in an IOT environment: the connected house would thus automate the activation of electronic and energy-intensive devices (washing machine, radiators, air conditioners, electric cars...) to time intervals where price and energy production are the lowest.
Moreover, this application could be implemented into the smart grid to gather information from the electrical network to help creating energy management systems.
These applications are doubtless interesting but they require much more time to be developed.

Overall the whole app can be improved in man different ways with different policies and its technical core should induce an in depth analysis to be able to deploy the final product.

Chapter 8

Conclusion

This research paper focused on finding a mobile-based solution to help people to respect the environment.
Such topic was chosen for the fact that nowadays a great number of people are concerned about the impact pollution is having on our planet and the consequences on their health. People have therefore been starting to adopt a sustainable lifestyle and now expect most of the companies to start being aware of the phenomenon as well. As a result, in the last few years we witnessed a lot of new products and services, which aimed at being more eco-friendly.
The work we discussed in this report was focused in the energy field, more precisely on consumption of electricity for residential purposes. We realized a static prototype of a digital application that aim at notifying users when the consumption of electricity will be at its lowest. This will help global warming aware people and those who wants to save money.

Machine learning is an always evolving field with constantly new processes. We thus proposed a method amongst lots of them but it can naturally be enhanced and even become obsolete quite rapidly.

Regarding the interface, as it's possible to get from what presented in this paper, design is not only art but it's first and foremost, an act of communication. For this reason, we pointed out how psychological principles play an important role in this field and they revealed to be an effective tool in design for making the creative process more productive and keeping the users committed.
From a functional point of view, we noticed simplicity is the key. Minimalist interface and other design techniques are certainly a way to achieve good design, but it is not the final goal. The ultimate aim is to simplify the interface in order to make it more functional and usable. It was highlighted also how every element of the design matters. Attention to small details can deliver big and powerful results enhancing the product design. For instance, the choice of the right colours and the animations increase the likelihood users stay committed. Moreover, all the guidelines, which were exploited in this work, are not stand-alone but they are related to each other. Furthermore, these principles can be applied in several fields and not only in the UX & UI design, such as in the software development.

For future developments the' ManEl' app could be extended with many other features as we discussed previously in order to help us give a more efficient answer to our concerns.

Eventually we can answer the question : "How can we help people manage their electricity consumption for the sake of the environment ?".
We therefore proposed a method that can be enhanced but formulates the basics of a work that can help people change their habits for environmental purposes regarding their electrical consumption.

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Appendix A

Appendix

A.1 Machine learning

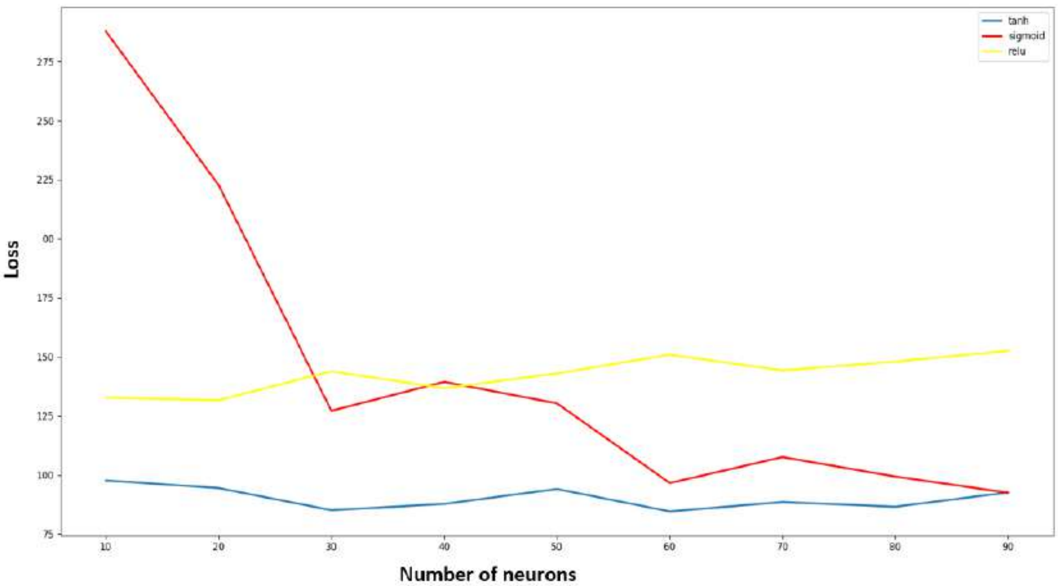

Figure A.1: Loss of the model for different amount of neurons depending on the activation function used

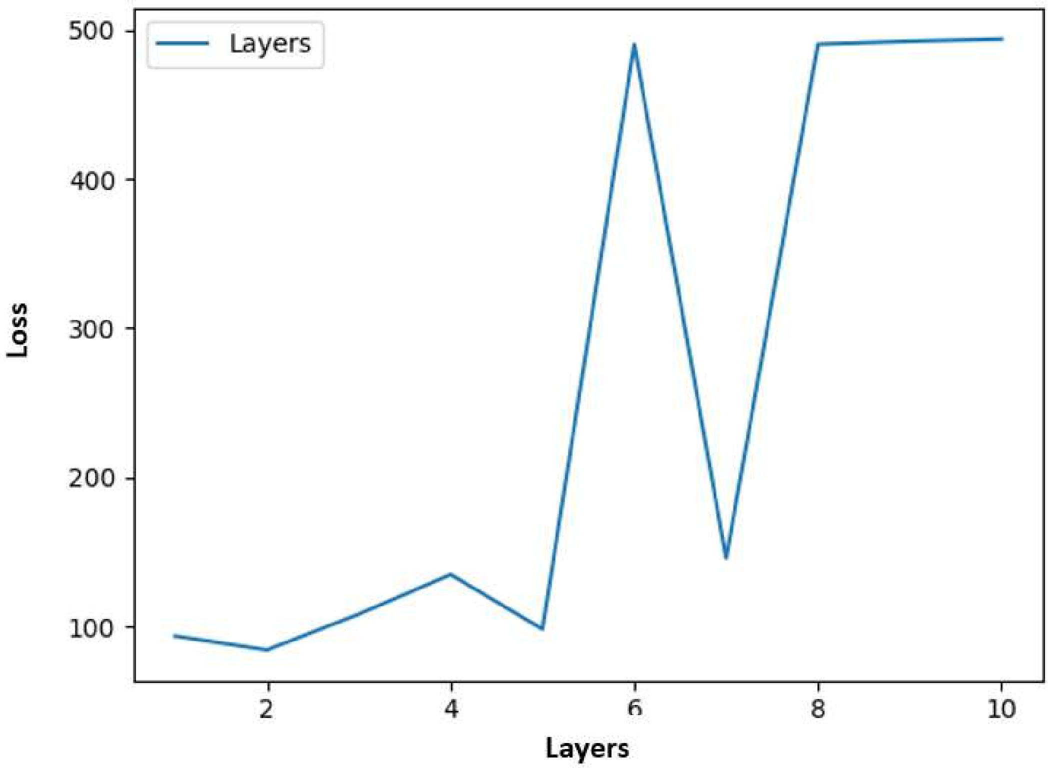

Figure A.2: Loss of the model for different amount of layers used

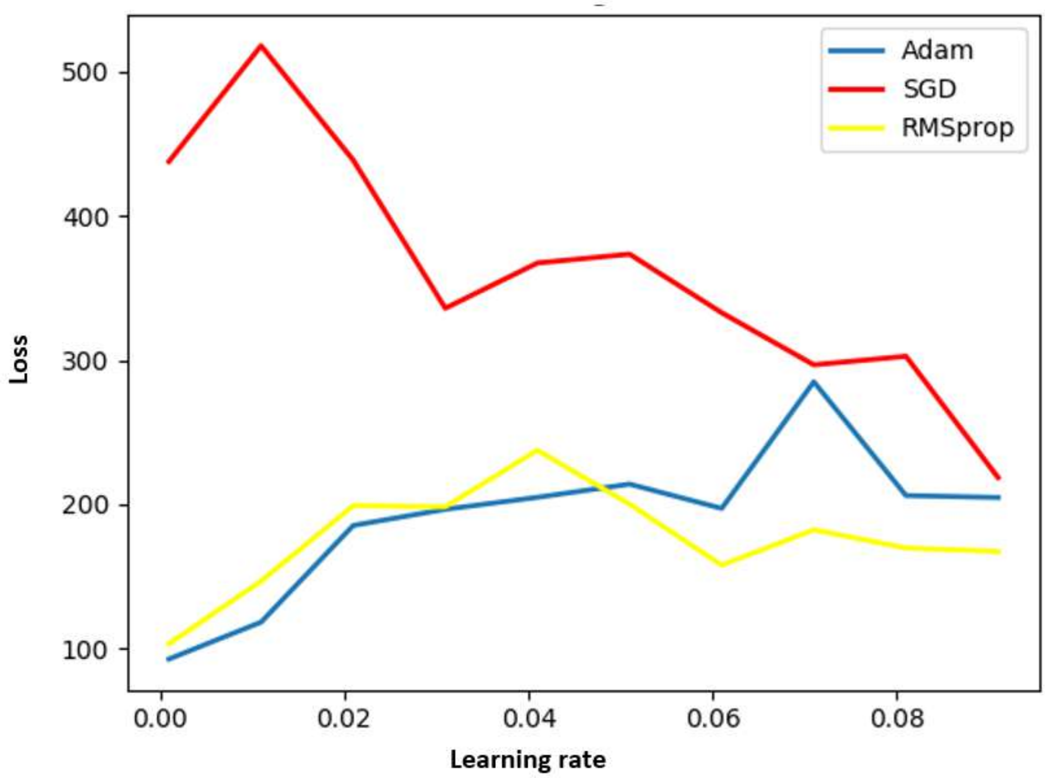

Figure A.3: Loss of the model for different Learning rate depending on the optimizer chosen

A.2 User story

In the interview with the users, one of the tasks for the users was to find out the predictive lowest time slot and to put a reminder in her calendar as a laundry day. We tracked users' steps during the task. Their sequential actions were then turned into a story to understand the user scenario.

Monika opens the ManEL (Mange your Electricity) app. She types her location. She also has an option to allow the app to locate her but she chooses to type the location manually. The app displays her lowest consumption rate time slot of that current day. She wants to get an overview of this week, so she selects the week button and views the overview of the electrical consumption graph for a week. She then picks a time where the electrical consumption is forecasted to be low, then puts a reminder on her calendar to do her laundry.