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BC4P

EUROPEAN UNION
European Regional
Development Fund

ACTUAL REALISTIC DISTRIBUTION DATA

[Sous-titre du document]

Version Tracking, will be removed in final document.

Version	Description	Author	Date
0.1	Initial draft.	Prakash Gupta, Pietro Piccini, Stefano Bromuri	13/03/2023
0.2	Final version	Prakash Gupta, Pietro Piccini, Stefano Bromuri	02/04/2023

PXL
LIÈGE université
howest
FH Aachen University of Applied Sciences
Tiorc
Open Universiteit
ZU YD
MIJNWATER, BASIS VOOR DUURZAME ENERGIE WWW.MIJNWATER.COM
CITIES
CAP CONSTRUCTION

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1 Introduction

The ability of trading energy in a P2P network poses challenges concerning the type of energy and data stored to operate a microgrid, as well as the money exchanged by the prosumers. Blockchain technology offers a mean to deal with tracking transactions, money exchange and preferences of the users, making it a perfect medium of interaction to build P2P energy trading.

The Grid singularity framework that is used as a backbone of the BC4P project, allows for a number of different market types. Specifically, in the BC4P project we make use of a two-sided Pay-as-Bid market.

As reported in the Grid Singularity Framework documentation "In a two-sided Pay-as-Bid market, buyers are able to place bids in the market, alongside the offers placed by sellers.

Each market collects and matches bids and offers issued by trading agents, and dispatches bids and offers to other markets via a MarketAgent, which is created and operated by each market (area). "

In addition to market mechanism itself, the grid singularity framework also allows for basic trading strategies to match offers and bids. The purpose of this deliverables is to describe realistic data set associated with the BC4P project. The various pilot sites of BC4P will have a topology associated with the assets that can produce, consume of "prosume" energy. This deliverable selected one of the pilots of BC4P to exemplify the type of data collected and the energy exchanged by the devices.

As a consequence this deliverable contains an exploratory data analysis of the PXL pilot, looking at the signature of the assets in such a pilot and their behaviour as time series.

In addition, this deliverable focuses on defining a trading model that extends the blockchain smart contract trading model described in WP2.T2, by including preferential trading amongst prosumers, given a potential social network inside the microgrid in which the energy exchange takes place.

Such a trading model leverages on the SoulBound NFT developed in WP3.T2, by including the concept of preference in the NFT.

The rest of this deliverable is structured as follows: Section 2 discusses relevant related work concerning trading models on the blockchain; Section 3 proposes an inventory concerning the data collected in the pilots that will take place in WP4; Section 4 discusses an exploratory analysis for the data of PXL as a realistic example of the data collected in BC4P; Section 5 discusses the Smart Contract extension to include user preferences in the trading model of BC4P and show the effects of including such preferences; Section 6 shows an evaluation using a preference model for the exchange, Section 7 concludes this deliverable and draws the lines for future work.

2 Related work on energy trading models on the blockchain

This section discusses relevant approaches towards P2P energy trading and how BC4P advances the state of the art with respect to such related works. For a more complete

Survey on blockchain enabled microgrids, we refer the interested reader to contribution of Wang et al (Wang2019).

Wu et al (Wu2022) discuss the socio technical interactions that needs to take place between stakeholders in order to make P2P trading a reality and how the blockchain can help this process. With respect to (Wu2022) this contribution goes one step beyond as it defines a proposition on how the stakeholders can be represented in the blockchain by means of Soulbound NFTs including trading preferences among the actors exchanging energy in the blockchain.

Esmat et al (Esmat2021) proposed a framework based on ant colony optimization to reach a global welfare. The application of Esmat et al also uses smart contracts to model transactions on a blockchain. With respect to this contribution, BC4P introduces the concept of preferences in the trading between the users, allowing the users control over how the energy and monetary value is exchanged. In addition, assets and customers are represented by means of NFTs with properties, that allows to modify how the transactions take place in the blockchain.

Jamil et al (Jamil2021) specify a trading energy platform based on blockchain and deep learning. The deep learning model defined uses recurrent neural networks to take decisions concerning energy tokens that may be produced one day ahead. With respect to (Jamil2021) this contribution does not consider machine learning models, but it rather focuses on the possibility of specifying preferences between assets owners, to mimic the behaviour of a social network, including smart contracts that go beyond the concept of producing transactions in a microgrid. In addition, BC4P is an extension of the GSY framework, that ensures that a balance is kept in the microgrid. As such, the work of Jamil et al could be combined with the framework defined in BC4P by extending the agents of BC4P to include a reinforcement learning component.

AlSkaif et al (AlSkaif2021) discuss two trading strategies in a blockchain based microgrid. The first strategy matches surplus power supply and demand of participants, while the second is based on the distance between them in the network. The smart contracts defined in the BC4P solution can generalize the results proposed in (AlSkaif2021) by means of a preference-based system associated with the owners of the assets. In addition to being able to specify the same strategies as in (AlSkaif2021) BC4P can also include constraints on the transactions that would redefine how the monetary exchange takes place in the blockchain.

3 Inventory of data sets available in BC4P

The purpose of this Section is to discuss the assets that produce data at the different pilots of BC4P platform. Specifically, BC4P has five pilot cases studies: PXL, Liege, Aachen, Eupen and Tiorc. In this Section we discuss the assets of the PXL and Aachen case studies. We leave the discussion concerning the other pilots to the WP4 work packages, and in here we limit ourselves in discussing the realistic power signature of some of these devices for the purpose of discussing the trading model with preferences in Section 5. The assets are of two types: consumers and producers. Batteries can work as consumers or producers, depending on the current amount of energy stored.

3.1 Assets in the PXL pilot

The PXL space consist of 15 consumer devices, and producers are mostly solar panels installations. This pilot includes high power machines associated with a maker space in the PXL building, where citizens meet for small projects. A list with a description of all items is presented below.

Embroidery Machine: a macchine to print on fabric.
LaserBig: This is a laser cutter to engrave big pieces of wood and metal.
LaserSmall: this is a small laser cutter.
MillingMachine: a 3 axis milling machine to modify metal or wood.
PcLaserBig: A big laser engraver for big pieces.
PcLaserSmall: A small laser engraver.
PcUltimakers: this is a professional 3D printer.
PcVinylEmbroid: this is a machine to print on fbaric.
PcbMilling: this is a 3 axis milling machine.
Photostudio: this is a machine to develop photos.
SheetPress: this is a sheet press to print on paper.
Ultimaker3Left: this is a 3D printer.
Ultimaker3Right: this is a 3D printer.
UltimakerS5: this is a 3D printer
VacuumFormer: this machine is used to put merchandise under vacuum.

Section 4 discusses the realistic profile of energy consumption of some of these assets.

3.2 Assets in the Aachen pilot

This pilot represent standard appliances that can be found in a house, such as a freezers, fridge coffee machine and so on, and it represent the energy consumption taking place at the workplace in FH-Aachen. A list with a description is available below. Also in the case of the Aachen pilot, producers are represented mostly with solar panels.

Freezer: this is a standard house fridge.
Fridge: this is a standard house fridge.
Trockenofen: this is a high temperature oven.
Fume hood: this is a ventilation system for fumes in a laboratory.
zentrifuge_gro√ü: this is a high speed centrifugue.
arbeitsplatz_zentri: this is the energy consumption of work space.
arbeitsplatz_photometer: this is the energy consumption of a photometer in a work space.
arbeitsplatz_laptop: this is the energy consumption of a work space decidacted to a laptop.
abzug_oben: this is an induction oven.
abzug_unten: these are induction cookers.
steckdosenleiste-kaffemaschine: This is a standard coffee machine.

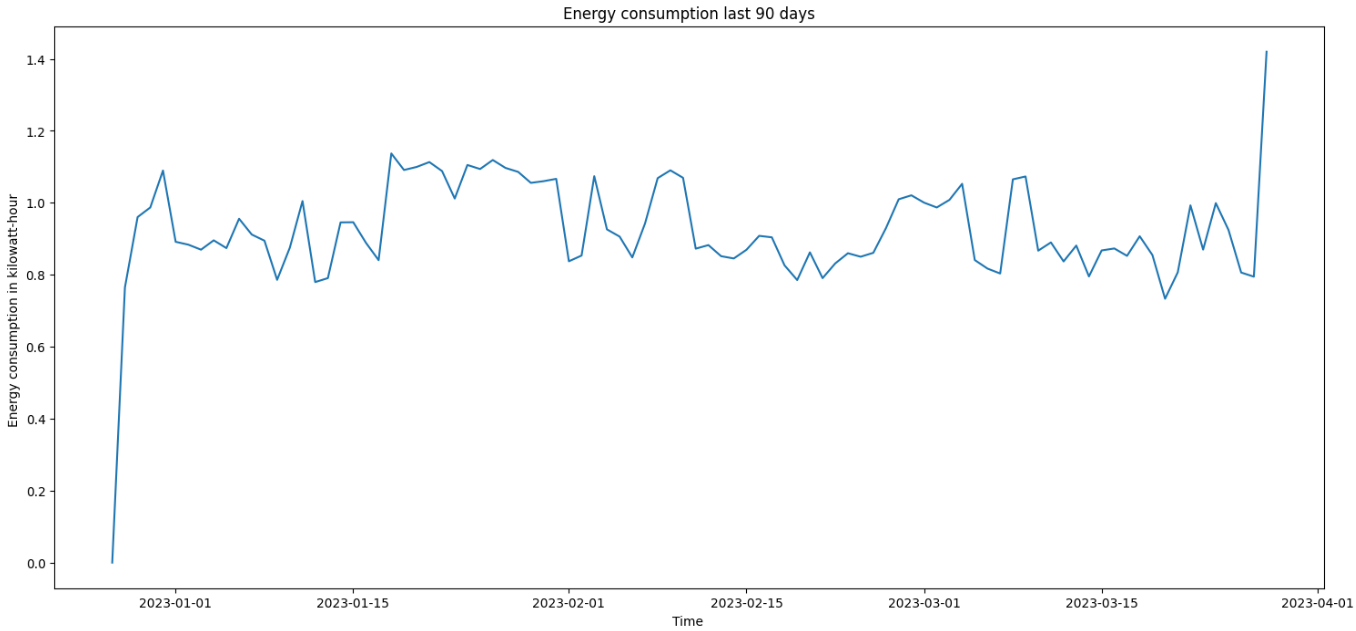
Section 4 discusses two examples of appliances coming from this pilot.

4 Exploratory data analyses

This Section discusses realistic energy curves produced by appliances in the PXL and Aachen pilots. We selected two small appliances and two high-power appliances from the two pilots in order to illustrate their realistic energy cycles. Specifically, we focus on reporting statistics concerning yearly consumption. Still, we report the activity of such appliances within a week, as these appliances typically present a seasonal behaviour with the season period within a week.

4.1 Aachen Fridge Appliance

The energy consumption of a fridge is usually measured in kilowatt-hours (kWh). The energy consumption of a fridge can vary depending on several factors, such as the size and age of the fridge, the ambient temperature, and how often the fridge door is opened. Generally, the energy consumption of a fridge is highest when it is first turned on, and then it stabilizes at a lower level once it reaches its operating temperature. A typical fridge appliance consumes around 1 to 2 kWh of energy per day, depending on its size and energy efficiency. The energy consumption of a fridge can be monitored using a smart plug or a home energy monitoring system. In the case of this appliance, we can see that in the figure 1

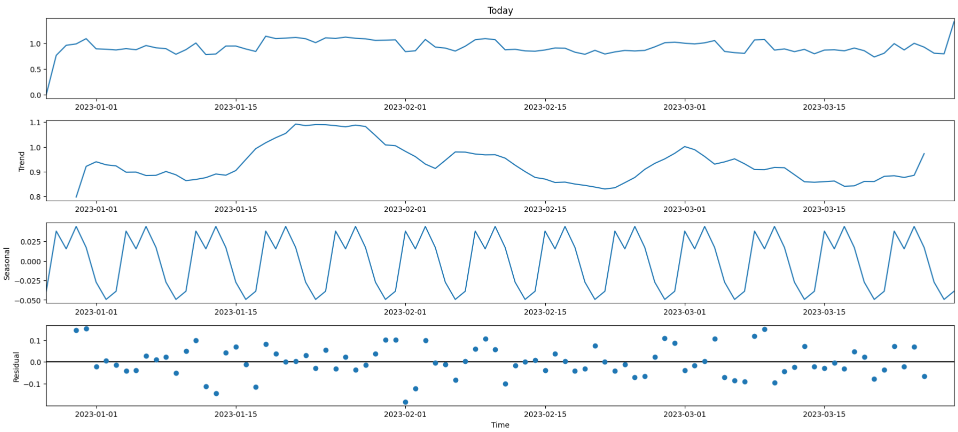


The refrigerator is one of the most energy-intensive household appliances, and its power consumption patterns can have a significant impact on overall energy usage. To better understand how the fridge is using electricity, we analyzed data from the past 90 days, measuring its average daily power consumption.

Our analysis reveals that the fridge's power consumption follows a distinct daily pattern. During the day, when people are more active and opening the fridge more frequently, the consumption tends to be higher. At night, when the fridge is opened less frequently, the consumption decreases.

Additionally, there is a clear weekly pattern, with consumption being higher during weekdays than weekends.

To visualize the trends and seasonality in the fridge's power consumption, we created a graph showing the interval time data. The trends show that the consumption increases during the first 15 days of the interval and then gradually decreases over time, reaching its lowest point towards the end of the interval. Meanwhile, the seasonality shows that the fridge consumes more power on weekdays than weekends, suggesting that people's daily routines have a significant impact on its usage patterns.

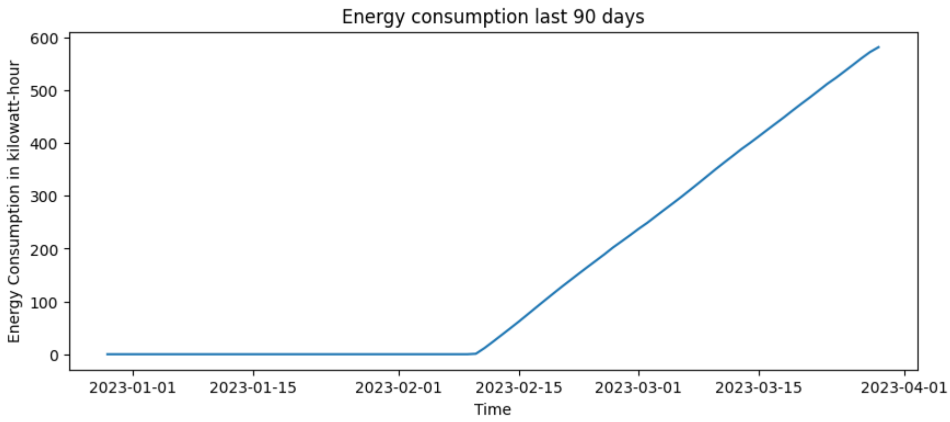


Given its patterns, we can expect that when interacting with the BC4P blockchain the fridge will produce more bids during week days and potentially a preference specifying that energy production from close sources closer in space would make more sense given the fact that it is an appliance that works on continuous basis.

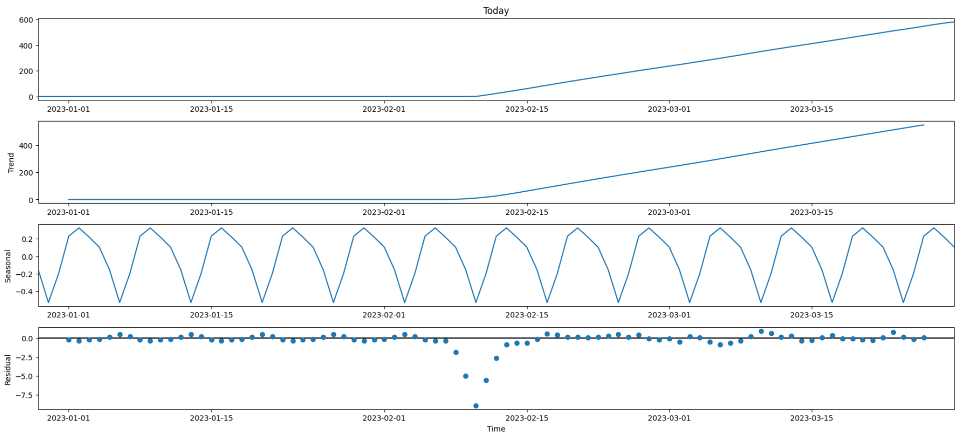
4.2 Aachen High Temperature Oven

The energy consumption of a high-temperature oven can range from around 100 to 1000 kWh per hour, depending on its size and heating capacity.

Generally, high-temperature ovens consume more energy than conventional ovens because they need to reach and maintain much higher temperatures.



Based on the information provided, it can be concluded that the Oven began collecting data on February 8th, and thus data from earlier days is not available. The graph displays the average daily power consumption of the Oven. The data indicate that on the first day of data collection, the Oven consumed the continuous high energy as compare to previous days. Following that, on average, it consumed approximately range from 100 kWh to 700 kWh per day and assuming that it will increase further as per the data.



The second graph illustrates the Oven's power consumption trends and seasonality. The trend indicates that the Oven's power consumption has been increased, with the curve rising. For seasonality, it is apparent that the consumption of power by the Oven increased each day, and its not easy to understand the consumption of energy.

To further analyze the data, it would be useful to compare the Oven's power consumption hourly vs day. Additionally, examining the time of day when the Oven is used the most could provide insight into the Oven's power consumption patterns.

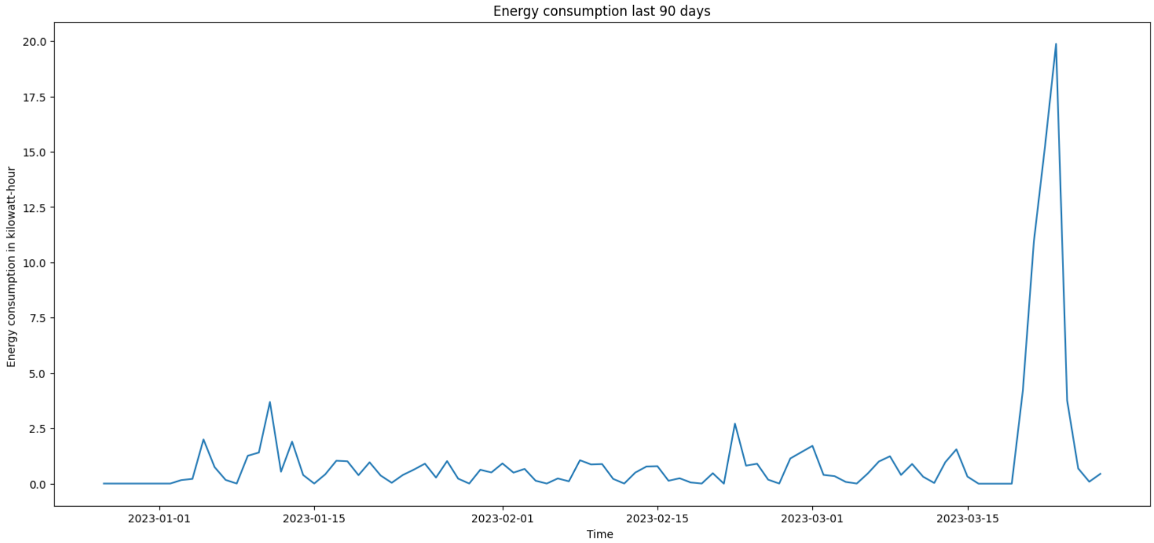
With respect to the BC4P blockchain, the high temperature oven tends to require more power at specific days, so we expect that the bids for energy will concentrate around peak power consumption when the oven is in usage in the Aachen facility.

4.3 PXL Laser Cutter

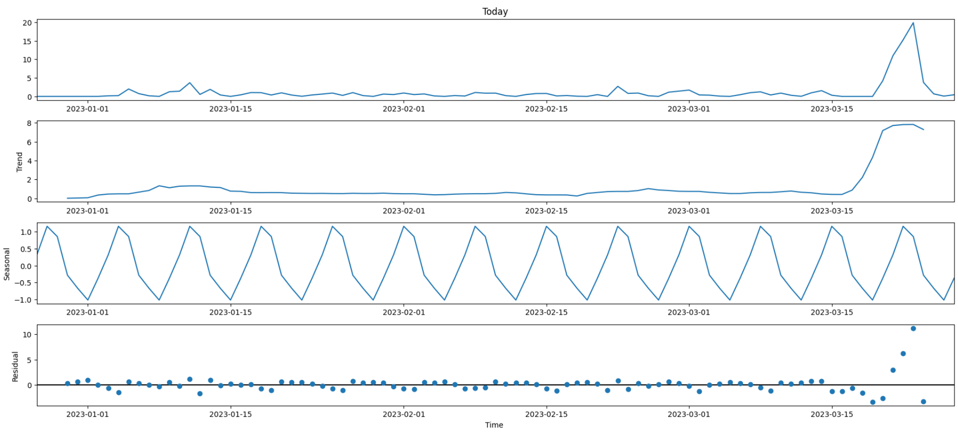
The energy consumption of a laser cutter can range from around 1 to 20 kWh per hour, depending on its power rating and usage pattern.

In addition to the power rating, the cutting speed and duty cycle of the laser cutter can also affect its energy consumption. The cutting speed is the rate at which the laser beam moves across the material being cut, while the duty cycle is the percentage of time that the laser cutter is actively cutting. A higher cutting speed or duty cycle will typically result in higher energy consumption.

The graph depicting the power consumption of the Laser cutter at PXL over the last 90 days provides an insight into the usage pattern of the machine. Upon closer analysis, it becomes apparent that the Laser cutter has not been used consistently, and the power consumption varies from 1 to 5 kWh on a daily basis. The average daily power consumption ranges from 1 to 5 kWh, and there are instances where the machine has not been used for the entire day.



The second graph depicting the trends of power consumption provides further technical details regarding the usage pattern of the Laser cutter. The graph shows that the power consumption of the machine has a fluctuating trend, with periodic upswings and downswings. These fluctuations could be indicative of varying usage patterns or operational inefficiencies of the machine. Additionally, the graph reveals a seasonal pattern, with similar consumption patterns observed over specific periods.



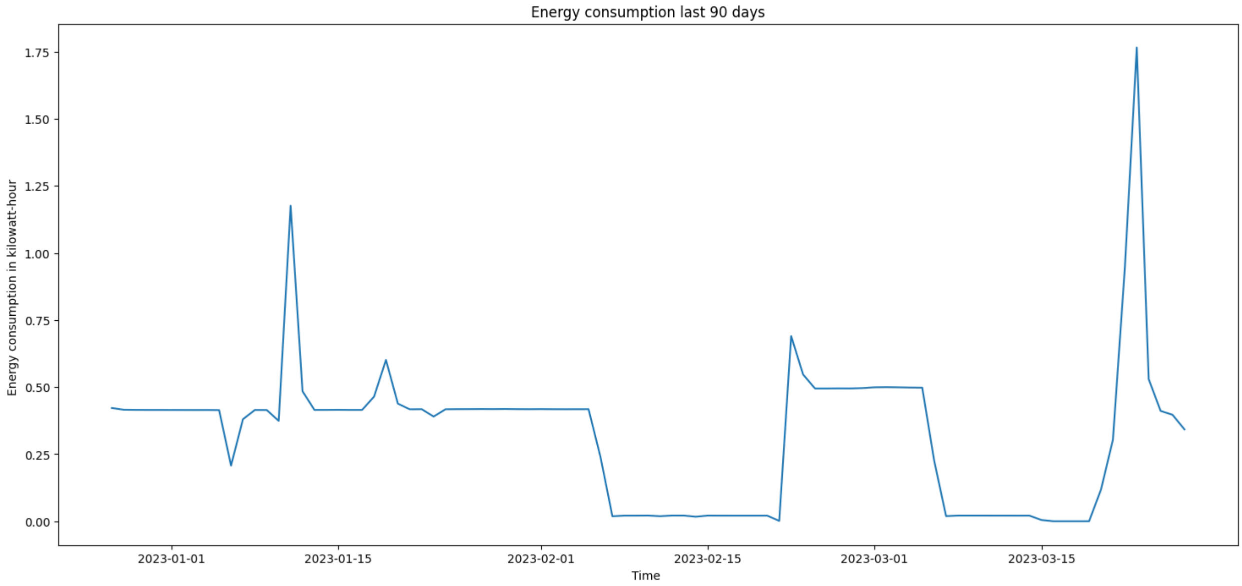
Similarly, to the oven, the laser cutter is used in specific weekdays in the PXL Maker lab, so it will show peaks in usage when the maker lab has visitors, that in any case come on a regular basis. Most often the laser cutter is not in usage during weekends, when there is a drop in energy usage.

4.4 PXL Milling Machine

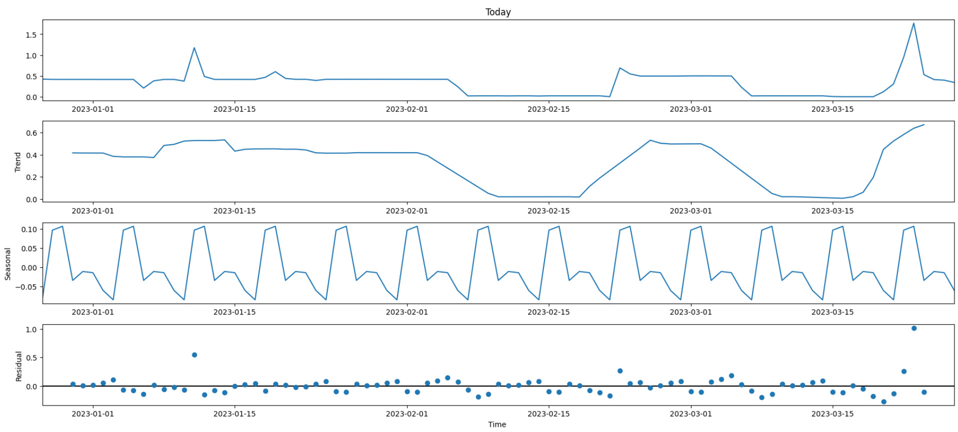
Milling machines are typically powered by electric motors, and their energy consumption is measured in kilowatt-hours (kWh) per hour of operation. The power rating of a milling machine can range from a few horsepowers for hobbyist-level machines to several hundred horsepower's for industrial-grade machines. The energy consumption of a milling machine can range from around too 5 kWh per hour, depending on its power rating and usage pattern.

In addition to the power rating, the material being milled and the cutting speed can also affect the energy consumption of a milling machine. Harder materials and higher cutting speeds typically require more power to achieve a given depth of cut. Additionally, the depth of cut can also affect energy consumption as deeper cuts require more force and therefore more power

The data of the milling machine show that the initially had continuous worked but in the given time interval the machine has offed for few days. The consumption of the power between 1- 2 kWh average per day.



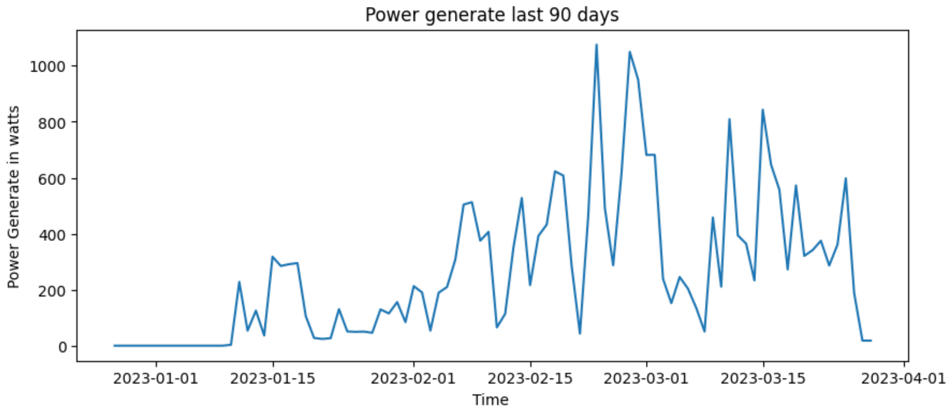
The trends show the consumption of power is almost the same daily excepts the days the milling machine was not used.



Such an appliance would produce constant bids to offers in the BC4P blockchains with a constant value concerning the power to be purchased.

4.5 Solar Power Installations, Energy production Curves

BC4P pilot in PXL has solar power data which provide the information of the PXL campus and pilot. Within BC4P solar power generators are considered energy producers and as such they can produce energy offers to the BC4P blockchain. The time series below show the energy produced by the solar panel in the last 90 days. Depending on the weather conditions and illumination, solar panels present an obviously seasonal pattern. In this case the production during Winter was captured, with low power in Watt productions.



In the case of BC4P, such an appliance is responsible to produce energy offers in the GSY platform discussed in previous deliverables.

5 Blockchain Trading model with preferences

This section discusses the extension of the basic trading model discussed in WP2.T2 and WP3.T1 by including a mechanism of user preferences in the smart contracts of BC4P.

Such preferences can be subdivided in the following categories:

- Spatial preferences: Spatial preferences occur when an asset owner, prosumer or producer, specifies a preference to negotiate energy within a maximum specific distance from the producer location.
- Social preferences: these preferences take place within a specified social network of an asset owner.
- Constraints associated with the hour of the day.
- Temporary Ad hoc agreements: temporal ad hoc agreements are specified P2P between an asset owner producing energy and an asset owner consuming energy.

Such agreements can be used to specify discounts on the energy sold to a specific consumer, or to specific a different energy price given the specific time of the day. In order to obtain such an adaptive behaviour, we modified the SoulBound token NFT defined in WP3.T1 to include metadata representing preferences.

```python
def add_asset_data(self, cons_asset, data):
    from . import Accounts
    print(cons_asset)
    account_id = cons_asset.account_id
    print(account_id)
    account = Accounts[account_id]
    current_data = self.soulboundNFT.image(account.address)
    json_data = json.loads(current_data)

    json_data[cons_asset.address] = data
    token_id = self.soulboundNFT.tokenOfOwnerByIndex(account.address, 0)

    self.soulboundNFT.updateMetadata(token_id, json.dumps(json_data), {"from": account})

    print(json_data)
    return current_data
```

The function above access a solidity contract deployed in the BC4P blockchain to store an json file containing the metadata of the preferences associated with the asset owner. When computing a bid against an offer of energy, the bid is now also evaluated in terms of its utility, computed with the function below.

```python
def highiest_utility_offer(self, asset, market):
    from . import ProducingAssets
    highiest_index = -1
    highiest_utitlity = 0
    for i, offer in enumerate(market.offers):
        prod_asset = ProducingAssets.existing(offer.original_market_address)
        print("prod_asset: ", prod_asset)
        prod_asset_data = self.get_asset_data(prod_asset)
        print("prod_asset data: ", prod_asset_data)
        u = self.compute_utility(asset, prod_asset)
        if u > highiest_utitlity:
            highiest_index = u
    if highiest_index != -1:
        return market.offers[highiest_index]
    else:
        return False
```

The computation of utility depends then on the metadata stored in the soulBound token representing the asset owner. The important thing is that now the offers are not only matched by means of the monetary value but also by means of their utility against the preferences specified by a user. More formally, cconsumer preferences refers to appliance energy trading preferences that each prosumer can specify for each asset. Such preferences include location, energy type (renewable, PVs, etc.) and price, among others.

One way to use preferences to make purchasing decisions is to have preferences that compute a utility function, then the offer with the highest utility function among all the offers available in the market can be selected to be purchased.

This way it is possible that a consumer that favors locally generated, renewable energy will purchase from an offer that matches such criteria even if the price is higher than other offers which do not match the criteria.

Each preference results are mapped to a single-preference utility value. A weighted sum of all single-preference utilities is computed to generate the final utility of an offer. The weights can be considered as a meta-preference which expresses a preference over the types of preferences. E.g. I might prefer a nearby energy source and I prefer it to be renewable, but the renewable preference is more important.

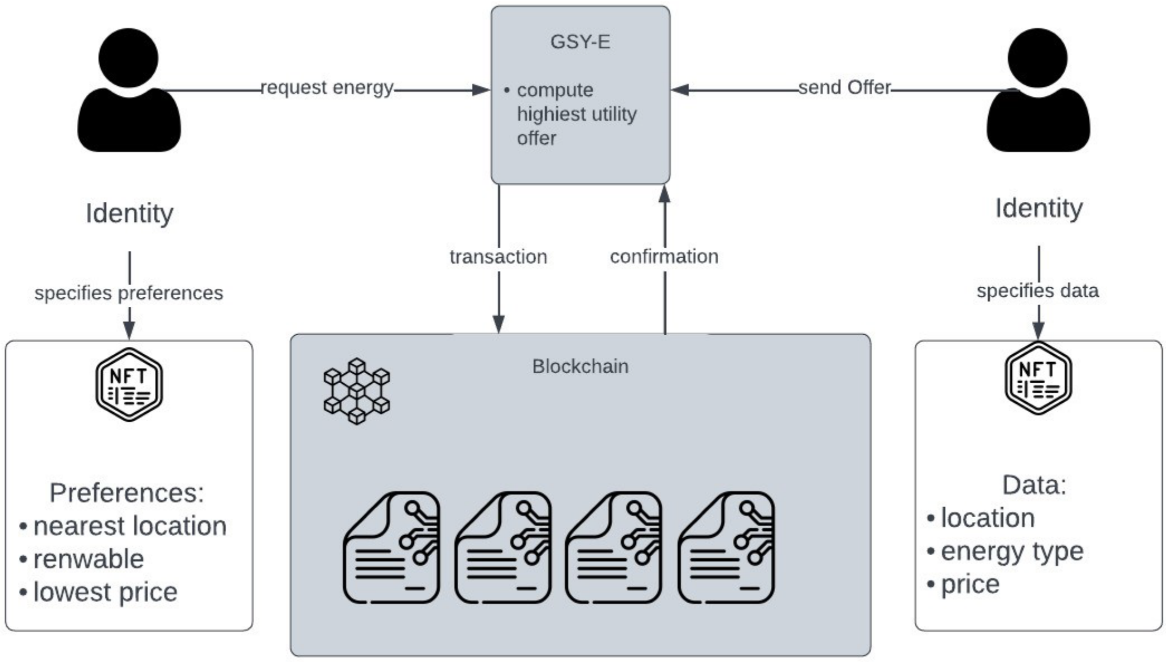
Finally, we have a utility function:

$$u(asset) = \sum \phi(\rho_i) * w_i$$

Where $\phi(i)$is the utility expressed as a function of an asset or bid information $p$and $w(i)$is the weight of that utility.

The preferences and asset information are stored in the soulBound NFT token together with the user data. Once a new bid is sent into a market all of the available offers are retrieved from the smart contract. Then, since the offers are mapped to assets and the assets are mapped to owners with a digital identity, the data is retrieved for all of the owners from their soulBound NFTs.

With all of the preferences is possible now to compute the utility of each preference and select the highest one. A transaction request is then sent to the market smart contract to exchange the money.



6 Results

A simulation was run to test the preference-based energy trading approach. In this simulation the asset data and user preferences are generated using the data of the PXL pilot to simulate a real user. In reality the preferences would likely be set by the user or inferred from user actions, in this case they are pre-set at the beginning of the simulation

```
offer/prod asset data:
location: [1.821932029194105, 1.5870918761070776]
type: renewable
offer price: 0.1375


cons asset data:
location: [0.3782688723103187, 1.2154983858908992]
type: non-renewable
offer price: 0.1375


location utility (distance): 1.4907196357849122
type utility: 1
price utility: 0.1375
weights: [0.6838533280510549, 0.9070092014435789, 0.0768140998261625]
final utility:
 0.6838533280510549*1.4907196357849122 + 0.9070092014435789*1 + 0.0768140998261625*0.1375 = 1.9370047242922448
```

Above is an example of how the utility was computed for the offer with the highest utility.

The location is represented as a tuple representing the latitude and longitude of the asset. The location utility can then be calculated as the Euclidian distance between the producing asset's location and the consuming asset's location. The type location utility is either 1 if the producing asset has the preferred type and 0 if it is different from the preferred type.

The price utility is simply the price of the offer. We assume that for any consumer a higher price is not preferred to a lower price. The final utility is then computed as the weighted sum of all utilities. The weights represent a meta-preference which describes which preferences are more important to the consumer.

If a second offer was sent to the market with the same price and the same asset data, but a closer location. Then the final utility would end up as a higher value and such offer would be selected for a transaction over the current offer.

7 Conclusions

This deliverable presents the data collected within two of the pilots of the BC4P project and how this is used to create a realistic simulation on how the energy and data in an exchange within an Ethereum compatible Blockchain, when preferences on the type of asset producing energy are specified concerning how to buy energy. Specifically, this deliverable shows how we extended the smart contracts developed in in T2 with preferences associated with the NFT representing the asset owners, and show how the trading model changes as a consequence of this preference based model.

Future work implies the definition of intelligent agents that can learn how to exchange energy and set preferences given societal goals such as increasing the utility of the energy exchanged with their neighbourhood. Such an extension would be possible in terms of model based agents, programmed by means of constraints and logic programming, or by means of reinforcement learning, both model free or model-based. The introduction of preferences could potentially make the learning process of these agents go beyond a simple trading model considering only monetary return, but also considering green goals by means of an automated specification of preferences in terms of goals set up by the community in which the energy exchange takes place.

8 References

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