HELIUS: A Blockchain Based Renewable Energy Trading System

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***Abstract*—This paper explores a peer-to-peer (P2P) sustainable energy exchange system using Blockchain and Deep learning algorithms. The main objective of this paper is to provide a general framework to design such a system with varying advanced components and their interaction. The proposed model is a novel mechanism for power system operations allowing users to trade energy during peak loads. The model also simulates sustainable energy production provided the system components and other respective variables for example location, time and weather. The proposed system is integrated with blind bidding mechanism and accompanying web application to demonstrate the feasibility in a real world environment.**

***Index Terms*—Blockchain,Peer-to-Peer,Deep Learning, Energy Trading, Clean Energy Exchange, Bidding Mechenism.**

I. Introduction

In 2018 the Global Economy consumed more than 23 terawatts [1] of electricity at an average price of $0.14 USD [2] despite maintaining 26.7 terawatts of electrical capacity [3]. There are more than $500 billion USD in savings available from a streamlined electrical network if the demand is managed at the edge of the electric grid. Consumers' electrical demand varies substantially over the course of a day and follows patterns which change over different times of the year. As a result of this inconsistency it is necessary for electrical utility operators to maintain excessive production capacity in order to be capable of meeting the peak electrical demand. As a result, this production capacity is often underutilized and results in additional financial costs that must be passed on to the consumer. Grid-edge solutions that allows for peer-to-peer energy trading provided an opportunity to meet the demand of consumers without the need to produce energy from fossil-based power plants. With advancements of electric storage solutions, electric vehicles, rooftop solar, and a wide variety of battery powered consumer products, it is now possible for individuals to trade energy among themselves based on demand and supply. However, electricity needs to get to the correct location at the correct time, and needs to be accounted for during the transaction. Furthermore, predictions are required to determine the local production and consumption of energy.

In this paper, we propose the Highly Efficient and Locally Integrated Utility System(HELIUS) to address the above mentioned problem. The HELIUS project aims to tackle this issue at both the individual and utility level by enabling a simpler exchange of electricity. This would allow electricity to be bought and sold similarly to oil and other physical commodities. Businesses can be built on the service of storing energy at times of reduced demand and price, while reselling that energy when there is greater demand. The result of this exchange is that the peaks and valleys of electrical demand can be leveled off to provide for a consistent market price that is maintained by long term market guidance, rather than near term consumer demand. Individuals could trade energy with neighbors based on if they have an excess or surplus of energy, and could buy and resell in order to balance demand and make money. In order to secure the tranaction and make sure that energy credits are accounted for in the sytstem, HELIUS uses blockchain technology for security and transparency of the transactions. Also, the system uses deep learning prediction algorithms to perform the prediction of energy production and consumption.

Similar projects are in development [4] [5], including digital tools from Power Ledger which enable customers, suppliers, and utilities to exchange energy and account for their interactions [6]. The HELIUS system will incorporate this functionality along side user friendly displays of information that enables individuals to make the exchange of energy that is appropriate for their needs.

The rest of the paper is organized as follow: Next section provides an overall of the system followed by the design approach in section 3. Section 4 provides the implementation of the system. Section 5 concludes the paper and provides direction for future work.

II. Proposed Model

This section will describe our proposed model and the high level interactions between the individual components of the HELIUS system. This includes the Blockchain, Prediction system, and the User Interface.

A. Blockchain

A distributed Blockchain ledger will be used to maintain an immutable record of the transactions and balances for the users in the HELIUS system. This will allow the users of the system to be confident that their transactions are being fairly recorded by a system that cannot be tampered with.

The HELIUS system can be implemented on a large or small scale, and the Blockchain implementation will be scalable

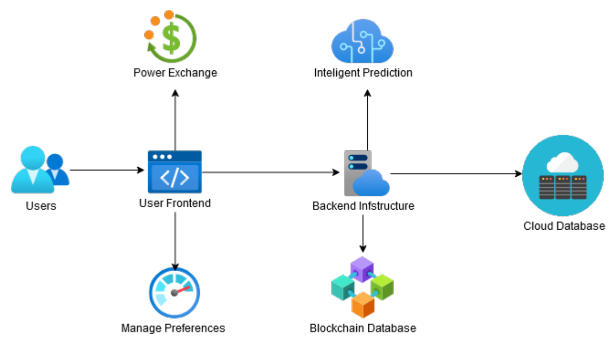

Fig. 1. HELIUS Trading System Overview

to handle the processing requirements that maintains the ledger. Users can be confident that the network will always be available to them because each node in the network will maintain a copy of the Blockchain. A failure at a single node will not be fatal to the system.

B. Prediction

In order to make an informed decision for trading energy, the user needs to know their energy production and consumption. The prediction system consists of a production model and a consumption model.

1) Production Model: The production model predicts the energy production for the day based on the longitude, latitude, panel information and weather conditions for the day. The parameters mentioned are used to simulate the optimal environment for energy production. The model receives user ID and based on that it extracts the address of the house and makes the prediction for energy production.

2) Consumption Model: The consumption model predicts the energy consumption for the day based on the users history of power consumption. Every household has a trained model based on their history of power consumption and is called based on the user ID to predict the energy consumption.

C. Bidding System

After the user posts their surplus energy production, other users with a deficit can bid on the energy postings. The bidding system validates the bid based on the users wallet size and the reservation price of the posting. The bid is only submitted if the bid is the first valid bid made on the posting or if the bid price is more than the previously submitted bid. When the postings are matured i.e. the time when the energy is available, the last valid bid is used to make the transaction.

D. User Interface

The user interface is responsible for all the elements that the user interacts with and is the starting point for all user engagement. Our system requirements directly influenced how the user interface is designed. Most logical functions have to be translated into a user interface element that initiates the function or displays the data necessary to execute that logic.

III. Design Approach

This section will outline how the components were designed to enable simple energy trading.

A. Blockchain

There are several key functionalities that the Blockchain nodes must perform to maintain the immutable record in this network.

1) Network Synchronization: When a node in the network collects a sufficient number of transactions to justify adding those transactions to the network, it must first mine that block to the network by computing the hash of that block using the information contained, as well as the timestamp of that block. The number of records accumulated before they are mined into a block should be variable, and will depend on a number of factors.

For the purpose of the scaleable HELIUS network, each block will accumulate a maximum of 500 transactions. When a Blockchain node reaches that threshold, it will mine the block to its network. Additionally, when 5 minutes have elapsed since that node last mined a block, and there are transactions pending, the node should mine the smaller block to its network. This higher frequency of mining ensure that networks with less activity can still maintain reasonable performance metrics.

Any time that a block is mined it will be distributed to the network, and these nodes will confirm the validity of the block's hash code and add it to their record.

2) Orphaned Block Re-submission: There can be the case that two nodes in the HELIUS network attempt to mine a different block to the network at the same time. In this case, each will contain different data and will be a separate fork to the block. When this happens, each node in the server should accept the first block it receives, and the subsequent blocks should be rejected because it does not contain the correct hash based on the block that was accepted.

This results in the network being forked, with different nodes containing a different node at the end of its network. When any node rejects a block, or when the originating node is notified that its block was rejected, the network will engage in a majority voting algorithm to determine which block will be accepted. Whichever block is not accepted will be mined to the network following the block that was accepted.

3) Majority Voting Mechanism: When any node is uncertain of its blockchain contents, such as when it rejects a block that contains an incorrect hash code, that node will request a copy of the ledger from all other nodes in the network. It will then accept the version of the blockchain which is agreed upon by a majority of all other nodes in the network.

In the event that this is the result of an orphaned block this will cause each node in the network to change their record to that of the most accepted version of the blockchain. In effect, whichever block was received first by the majority of the network will be accepted. The orphaned block would then be added to the network after the accepted block.

B. Prediction

1) Production: The production model [7] uses the user's address and panel information such as number of panels and size of panels to calculate the total energy that can be produced by the user. The model first calculates the angle of declination of the sun. The declination angle, denoted by δ, varies seasonally due to the tilt of the Earth on its axis of rotation and the rotation of the Earth around the Sun. The Earth's equator is tilted 23.45 degrees with respect to the plane of the Earth's orbit around the Sun, so at various times during the year, as the Earth orbits the Sun, declination varies from 23.45 degrees north to 23.45 degrees south.

$$\delta = 23.5 * sin(360 * (284 + n)/365) \tag{1}$$

Where δ is the declination angle, n is the number of the day of the year. After calculating the declination angle, the system calculates the height of the sun based on the time of the day and solar noon. Solar noon is the moment when the Sun passes a location's meridian and reaches its highest position in the sky.

$$h = arcsin(cos\phi * cos\delta * cos(15 * (T - T_o)) + sin\phi * sin\delta) \tag{2}$$

Where T is the time of the day and T_o is the solar noon, ϕ is the geographic latitude of observer i.e. the solar panel in our case. The total solar radiation on a horizontal surface taking into account the direct and scattered radiation is determined by the formula

$$Q_o = (0.625S + 0.68) * sin(h) \tag{3}$$

Where S is the intensity of solar radiation, for simplicity S = 1 kW/m^2. One of the most important factors while calculating the solar radiation on a surface is the Azimuth angle. The azimuth angle is the compass direction from which the sunlight is coming. At solar noon, the sun is always directly south in the northern hemisphere and directly north in the southern hemisphere. The azimuth angle varies throughout the day and is calculated using the equation below.

$$A = arcsin(\frac{cos\delta * sin(15(T - T_o))}{cos(h)}) \tag{4}$$

Equation 5.3 does not consider the consider cloudiness. Incoming of solar radiation on a horizontal surface taking into account the cloudiness can be calculated by

$$Q_r = Q_o(1 - 0.38 * (1 + k/10) * k/10) \tag{5}$$

Where K is the cloud cover for the day. In the end, in order to calculate the amount of solar radiation falling on an inclined surface i.e. a solar panels can be calculated by

$$Q = Q_r(\frac{cos\alpha * sin(h) + sin\alpha * cos(h) * cos(A)}{sin(h)}) \tag{6}$$

Where α is the angle of inclination from the ground. After calculating the total solar radiation falling on the solar panel, the model calculates the total amount of energy generated by the solar panels.

$$Power = Efficiency * area * Q * (1 - 0.005(Temp - 25^oC)) \tag{7}$$

2) Consumption: The consumption model predicts the user's consumption for the day based on their previous history of consumption. The dataset used in our implementation was provided by UMass Trace Repository [8] to train time series model in order to predict the energy consumption. Before the models were trained, thorough data cleaning, analysis and preprocessing was performed.

3) Data Cleaning: The dataset contained energy consumption of a house from 3 different meters from 2014 to 2016. One of the major issues was the irregular frequency of the measurements and lack of documentation in the data repository. In order to merge the data collected from the 3 meters, the missing values were interpolated and then the datasets were combined. The process was repeated for data collected for every year and later all the years were combined to make a unified dataset with hourly frequency i.e. data was collected at 1 hour intervals.

4) Data Analysis:

- **Test for Stationarity** - A common assumption in many time series techniques is that the data are stationary. A stationary process has the property that the mean, variance and autocorrelation structure do not change over time. In order to test our hypothesis, we used the *Augmented Dicker Fulley test*. The test is used to check if the data is stationary. The null hypothesis of the test is that the time series can be represented by a unit root, that it is not stationary (has some time-dependent structure). The alternate hypothesis (rejecting the null hypothesis) is that the time series is stationary. We interpret this result using the p-value from the test. A p-value below a threshold (such as 5% or 1%) suggests we reject the null hypothesis (stationary), otherwise a p-value above the threshold suggests we fail to reject the null hypothesis (non-stationary).
  From our results we can conclude that our data is stationary.
- **Autocorrelation and Partial Autocorrelation Function Plot** - ACF is an (complete) auto-correlation function which gives us values of auto-correlation of any series with its lagged values. PACF is a partial auto-correlation function is used to find correlation of the residuals with the next lag value. The ACF and PACF can be used to provide an intuition on which ARIMA model to use.

TABLE I
RESULTS OF DICKEY-FULLER TEST:

Test Stats	-6.033340e+00
p-value	1.400910e-07
# of lags used	4.900000e+01
Number of Observations Used	2.625400e+04
Critical Value (1%)	-3.430599e+00
Critical Value (5%)	-2.861650e+00
Critical Value (10%)	-2.566829e+00

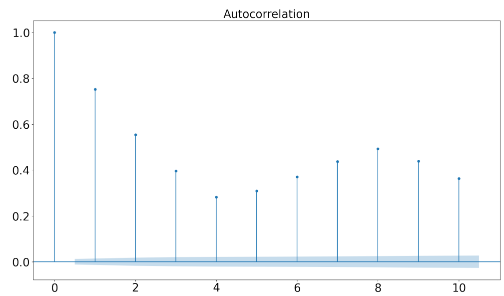

Fig. 2. Autocorrelation Plot

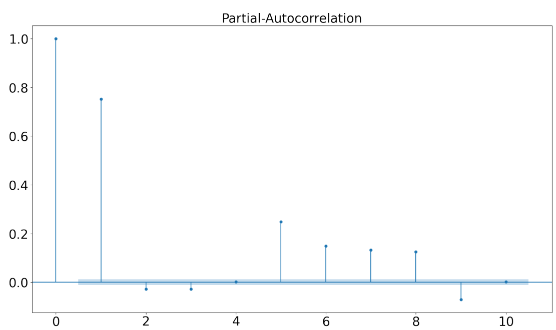

Fig. 3. Partial Autocorrelation Plot

Based on our results, We can conclude that an AR model of degree 1 is useful since our PACF drops after the 1st lag.

- **Heteroskedasticity** - Heteroskedasticity happens when the standard deviations of a predicted variable, monitored over different values of an independent variable or as related to prior time periods, are non-constant. *White's Test* was used to test for heteroskedasticity in the data. White's Test for heteroscedasticity is a robust test that tests whether all the variances are equal across your data if it is not normally distributed. The results of the White's test can be interpreted as that of Augmented Dicker Fulley. Therefore based on our results we tell that our data is heteroskedastic. Because of this issue, ARIMA models are not useful since they do not deal with heterskedasticity. In order to fix this issue, Weighted Least Square model was used. The model failed to fix the issue as well since the best R^2 value achieved was still 0.345.

TABLE II
RESULTS OF WHITE'S TEST

Lagrange multiplier statistic	1132.8926110728848
p-value	1.5364529349568804e-221
f-value	43.80122582243884
f p-value	9.880036839645724e-227

TABLE III
WLS REGRESSION RESULTS

Dep. Variable	y
Model	WLS
Method	Least Squares
Prob(F-statistic)	0.00
Log-Likeihood	8393.7
No. Observations	26299
Df Residuals	26292
Df Model	6
Covariance Type	Nonrobust
R-squared	0.344
Adj.R-squared	0.344
F-statistic	2299

- **Normality** - To test for normality of the data, *Anderson-Darling Test* was used. The Anderson–Darling test is a statistical test of whether a given sample of data is drawn from a given probability distribution, normal distribution in our case.
  Based on our results, we can conclude that the data is not normally distributed. In order to fix it we tried to use box-cox transformation but that was not able to fix that problem if normality either.

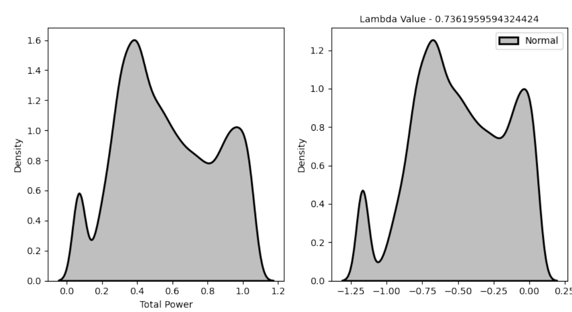

Fig. 4. Box Cox Transformation Result

Because of the issues mentioned above, a more robust time series model was needed. For the purpose of our system, we

TABLE IV
ANDERSON-DARLING TEST

Statistic	275.495
15.000	data does not look normal (reject H0)
10.000	data does not look normal (reject H0)
5.000	data does not look normal (reject H0)
2.500	data does not look normal (reject H0)
1.000	data does not look normal (reject H0)

TABLE V
MODEL PERFORMANCE METRICS

MSE	RMSE	MAE
0.0367	0.1916	0.1504

used a **LSTM** model which used a many to many sequence of predictions where the model takes in a 24 hour window i.e. the consumption from the previous day to predict the next 24 hours of consumption. The size of the model was restricted to 1 hidden LSTM layer to reduce the inference time. As we can see from the results, the model has an error of 0.15 to 0.19 kW/h error.

C. Bidding System

The bidding system implemented in HELIUS uses a blind sealed bidding algorithm and selects the highest bid for the posting at the time of its maturity or availability.The bidding system further interacts with the Blockchain to perform the transaction and notifies the two parties.

IV. IMPLEMENTATION

Our implementation combines all the previously design elements into a single seamless application designed to be accessible by the general public. The Blockchain, Prediction, and Bidding all operate seamlessly in the background while the user controls the functionality with we application accessible through any modern web browser. Figure 5 shows an example of what the user will see when the login which includes the production, consumption and calculated surplus for the day. Figure 6 demonstrates how the user will be offered to post their surplus energy on the marketplace while Figure 7 shows the postings currently available for bidding.

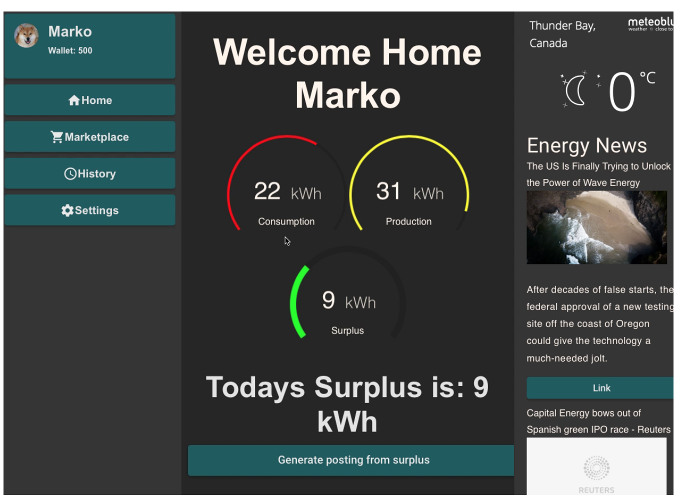

Fig. 5. Example homepage showing the users production, consumption and possible energy surplus which will be used as the surplus available for sale on the marketplace

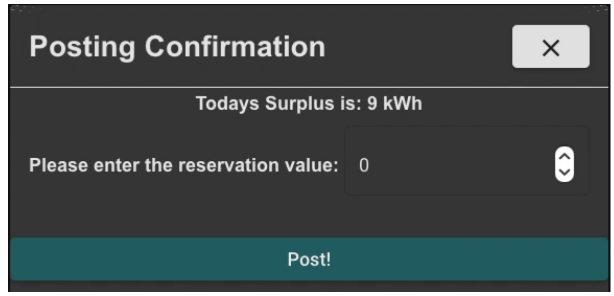

Fig. 6. User prompt window to post surplus energy on the marketplace

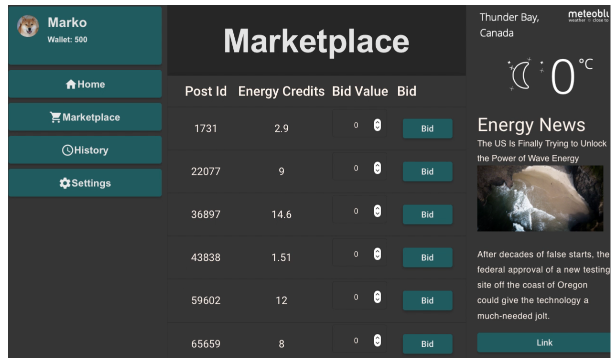

Fig. 7. Example marketplace showing currently available postings and the user option to enter bids

V. CONCLUSION AND FUTURE WORK

In this research paper, we propose and implement an energy trading system built on advance statistical analysis techniques for energy prediction while also employing a sealed bidding algorithm all secured by Blockchain technologies. By combining these methods, we can reduce the stress on the electric grid by distributing its storage and generation all while reducing the cost for residential users. Future work will include but not be limited to, implementing a more advance and reliable Blockchain framework, deploying more advance machine learning algorithms for energy consumption and production analysis, and iterating on interface designs to be more accessible.

REFERENCES

[1] N. Sönnichsen, "World Electricity Consumption," Statista. Feb 2021.
[2] J. Smith, "The Current Average Cost of Electricity Per Country," Host Dime. Feb 2021.
[3] IEA (2020)"Electricity Information: Overview," IEA, 2020.
[4] Pankiraj, Jema Yassine, Abdulsalam Choudhury, Salimur. (2020). Incentive-based Peer-to-Peer Distributed Energy Trading in Smart Grid Systems. 1-6. 10.1109/ISNCC49221.2020.9297278.
[5] Moniruzzaman, Md Khezr, Seyednima Yassine, Abdulsalam Benlamri, Rachid. (2020). Blockchain for smart homes: Review of current trends and research challenges. Computers Electrical Engineering. 83. 106585. 10.1016/j.compeleceng.2020.106585.
[6] "Power Ledger: Our Platform," Power Ledger, 2021.
[7] Platonova, Elena Toropov, Andrey Tulikov, Alexander. (2019). Simulation of Energy Input to Solar Panels. 133-137. 10.1109/URALCON.2019.8877633.
[8] Weibel, T. (n.d.). Umasstracerepository. Retrieved April 17, 2021, from http://traces.cs.umass.edu/index.php/Smart/Smart