Internet of Mobile Energy: Towards seamless energy trading across the transport and energy sectors.

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Abstract—The rapid growth in distributed energy sources on power grids is leading to more decentralised energy management systems for the prediction of power supply and demand and the dynamic setting of an energy price signal. Within this emerging smart grid, electric vehicles can serve as consumers, transporters, and providers of energy through two-way charging stations, which highlights the importance of predicting vehicle mobility and battery state of health to the effectiveness of decentralised energy management. This paper proposes a vision for an Internet of Mobile Energy (IoME), where energy and information flow seamlessly across the power and transport sectors to enhance the grid stability and end user welfare. Energy predictions that drive the price signals are used to guide electric vehicle mobility decisions, which in turn underpin the prediction of mobility patterns and future energy predictions. We propose an information architecture for IoME that incorporates data observations across all participants, a blockchain framework for data transmissions, and machine learning for energy and mobility predictions. We present an example scenario that details the seamless and closed loop information flow across the energy and transport sectors, along with a blockchain design and transaction vocabulary for trusted decentralised transactions. We finally discuss the open challenges presented by IoME that can unlock significant benefits to grid stability, innovation, and end user welfare.

Index Terms—blockchain, smart grid, transport, power quality

I. INTRODUCTION

The emergence of the two-way communication model and Distributed Energy Sources (DES) is transforming traditional power systems from largely centralised energy production to more decentralised and connected management systems, where all nodes can inject energy and communicate with other parties involved. This is called the smart grid. A broad range of devices connected through the smart grid can inject information to the network and communicate with the energy manager which in turn leads to the emergence of new services to facilitate energy management and prevent energy shortage and price fluctuation. As an example, the participating nodes in the smart grid can share their future energy demand or supply with the energy manager which is used to estimate the future energy demand or supply and thus forecast the energy price.

As the smart grid evolves, electric vehicles (EVs) are emerging as new unconventional and highly disruptive participants in the grid that can add significant benefit and flexibility. EV adoption in the USA, for instance, is forecast between 48% and 88% of the total consumer vehicle market by 2050 [2]. EV’s are conventionally viewed as energy consumers, where they are charged at charging stations to support their movement. Notably, EV’s are equipped with a relatively high capacity battery that stores energy to power the vehicle. EV batteries, coupled with the recent introduction of two-way charging/discharging stations [3], open up the possibility of EV’s to also serve as mobile energy transporters within an electrical grid and as energy suppliers to the grid when they have disposable energy. Such functionalities allow EV’s to contribute to helping service peak demand or voltage regulation within specific zones of the grid. This is particularly attractive as EV’s can have a battery capacity at least an order of magnitude higher than current home batteries.

The trends toward greater forecasting in smart grids, distributed energy generation and greater adoption and charging/discharging flexibility of EV’s highlight a greater convergence between the energy and transport sectors. The vision is a future where information and energy flow between the grid and electric vehicles is seamless and beneficial both to the grid’s stability and the end user’s interests. We refer to this vision as the Internet of Mobile Energy (IoME).

Realising the IoME vision requires a highly connected, secure and trusted communication infrastructure that supports the exchange of large volumes of data for the accurate prediction of future energy, that in turn guide decisions within this network. However, several challenges are involved to achieve these requirements: i) limited data sources: connected devices in the smart grid can only capture limited information about the energy generation or consumption, ii) scalability and overheads: transferring a large volume of data increases the packet overhead and bandwidth consumption and in turn limits the scalability. The conventional energy management frameworks rely on centralized brokered communication model which in turn creates a single point of failure and many to one traffic challenges; iii) data processing: the broad range of data collected from heterogeneous devices complicates the forecasting process; iv) security and privacy limitations: the increased connectivity of the smart grid devices, particularly with the emergence of EV’s, raises the security concerns where malicious nodes can compromise a device and inject fake information to the network which in turn impacts the decisions...
made by the managers and may disrupt the whole network. The devices collect privacy-sensitive information about the users, e.g., the energy consumption pattern, that enables the service providers (SPs) to build virtual profile about the user which in turn compromises their privacy.

In recent years, there has been extensive research toward addressing the outlined challenges through multiple technologies including blockchain, IoT, and machine learning (ML). To enhance the security and privacy of the smart grid and address the centralization challenge, blockchain has attracted tremendous attention due to its salient features which includes decentralization, security, anonymity, auditability and transparency [14]. Blockchain is a shared ledger of blocks where each block stores records of the communications between the participating nodes, also known as transactions. Each node is known by a changeable public key (PK) which introduces a level of anonymity. To enhance the adoptability of the blockchain for large scale networks such as smart grid and IoT, various lightweight blockchains have been proposed in the literature [5], [4] which increase the scalability of the conventional blockchains and significantly reduce the associated resource consumption.

To address the data processing challenges, ML algorithms that have been proposed [8], [7], [6] enable the energy managers to process data collected from heterogeneous sources and predict the future energy demand based on the history and current requirements of the nodes. Many of these prediction algorithms rely not only on energy grid data sources, but also on IoT sensor data to predict microclimate patterns [10], as well as external weather data to predict macroclimate [9], which both correlate with energy availability from renewable energy sources such as roof-top solar. While technology innovation is already disrupting smart grids, much of it is occurring in silos of activity which only considers the impact of either blockchain or ML in energy management. The convergence and tighter coupling of these technologies can provide a key step towards achieving the IoME vision.

In this paper, we propose a novel IoME architecture that utilizes IoT, ML, and blockchain technology to facilitate energy management. Our solution cuts across industry sectors by considering the mobility patterns of EVs in predicting and identifying energy prices. The IoME architecture enables all participants to communicate and share information in a trusted, secure and anonymous manner. The participating nodes exchange their energy supply or demand information to predict the future demand and supply of energy in the network. Energy prediction in the IoME architecture also utilizes the mobility patterns of the EVs as an input which enhances the accuracy of the energy demand or supply by considering the mobile nodes in the network. The data is processed using ML algorithms and the result is announced to the network as energy price signal.

The energy price signal is used by the participants in the transportation industry that includes EVs and ride sharing service providers (SPs), e.g., Uber, that introduces the following benefits: i) energy transportation: each EV is equipped with a battery and thus the vehicles can be charged in one place and discharge in another place that results in purposeful energy transportation. This is critical when the load in a particular area is increasing and may lead to the deterioration of power quality of the distribution system, ii) identifying a route toward a destination: where an EV or fleet of EVs can consider the energy price in deciding a route to reduce their cost, iii) ride sharing services: the SPs may use the energy price signals to identify the additional fee to the drivers that can either be reducing the cost of charging or energy transportation.

II. INTERNET OF MOBILE ENERGY

A. The IoME vision

The IoME future relies on seamless interaction between energy and transport agents. Figure 1 shows a high-level overview of IoME, in which the data of the IoT devices, smart grid participants, and EVs flow freely. In fact, the IoME vision calls for the blurring of information boundaries between the energy and transport sectors. The expected information flow in IoME is shown in Figure 2. Energy demand and supply predictions, based on grid, IoT, and weather data, determine the energy price signal. The price signal in turn will drive the mobility decisions of EV's within the mobility grid (transport network). Present mobility decisions will be used to predict future mobility, which will in turn feed into the prediction of future energy demand and supply.
We now discuss these steps in more detail, starting with predictions and decisions in the energy grid, followed by decisions and predictions in the mobility grid.

**Energy grid**

The main aim here is to predict the energy demand and supply in the network and thus provide pricing signals to balance the load in the grid and thus prevent energy shortage or oversupply, and to maintain the grid operational stability. We refer to the nodes that run the learning algorithm as learners. The energy grid operations within IoME involve two steps:

- **Energy Supply and Demand Prediction:** To predict the energy demand and supply the learners must gather data. The proposed framework introduces a broad range of data sources to enhance the accuracy of the energy demand and supply prediction which, as outlined in Section II-B, can be categorized as IoT devices, transport nodes and energy nodes. The IoT devices capture various data of the everyday life of the users which in turn can be fed into the machine learning algorithm to enhance the prediction accuracy, e.g., the calendar of a user can impact the future demand of a user. As another example, in a smart home, the input values to the learning algorithm can be information provided by the owner, e.g., the predicted home occupancy, DESs, weather prediction, etc. The building energy manager can enforce its predicted values to reduce the overhead in the main grid.

One of the key contributions of this paper is to consider the mobility pattern of EVs in predicting the energy supply or demand. EVs may need to charge in a charging station or they may have disposable energy that can be injected to the grid to balance the load, thus it is critical to consider the future mobility pattern of EVs to enhance the accuracy of the energy prediction. Mobility data for EV’s can be sourced through individuals or organisations opting in for receiving real-time energy pricing signals that can allow them to guide their movement decisions. Another mobility data source will be the recent docking information from all the charging stations, as well as city-wide data from local transport authorities and mapping services.

A critical data source that informs mobility and energy potential is the state of health (SOH) of EV batteries. The SOH not only determines the amount of energy each battery can contribute, but also the range of reachable charging stations based on its energy data. This group of charging stations constrains the search space for possible routes and destinations for each EV. All this data can be fused for the purposes of mobility modeling and prediction, which we expand on later in this section. The grid manager (GM) uses the mobility predictions, alongside the energy supply and demand predictions, to forecast the overall energy state in the smart grid.

- **Energy Price Signal:** Based on the predicted energy demand and supply, the GM identifies the energy price and releases price signals to the network. Recall that the data processing may happen in a hierarchical fashion. This feature enables multiple energy prices to be issued in different places, which will impact the mobility pattern as discussed below. The participating nodes may alter their energy consumption generation pattern according to the price signal.

**Mobility grid:** The outcome of the learning algorithm, i.e., the price signal is utilized by participants in the transport sector, mainly EV’s. Note that the energy companies may issue location-specific energy price signals, depending on supply/demand conditions, or grid stability requirements such as voltage regulation. The underlying energy transmission lines may be overloaded by the injected energy which results in power quality deterioration. To address this challenge, the managers of the transmission line may offer incentives to the EVs to transfer energy from one location to another. For example, a suburb whose transmission lines also serve as the connecting point for other surrounding suburbs may have an overloaded transmission line. EV’s can be incentivised to visit the surrounding suburbs to discharge energy in order to relieve the load on the loaded lines.

In conventional energy trading platforms, the energy provider must inject energy to the grid in exchange for a feed-in tariff, which is typically lower than the energy price that consumers pay for buying energy from the grid. This reduces the benefits of the energy producer, and may also lead to power quality deterioration as outlined above. To address this challenge, the EV may directly transfer the energy to the consumer which in turn increases the user gain. As an example, an EV may discharge its battery in a two-way charging station in busy suburbs where there is high energy demand in order to increase its gain.

The fundamental benefits of this for the transport sector are three-fold. First, the EVs can decide on a proper time to charge or discharge the electricity which in turn reduces the cost for the end-user. Second, the EVs travelling can consider the energy price signals and their mobility costs and constraints, such as traffic. They can either charge/discharge with low/high price, or function as energy transporters to transfer energy from one location to another location (within the route of the vehicles), which in turn helps to improve the power quality in the transmission line and reduces the chance of power shutdown. Third, the ride sharing companies can feed the pricing signals to their route decision making and price estimation algorithms to make their fleet of vehicles aligned with the market energy demand or supply and thus increase their revenue. The drivers may also consider the benefit gained from selling/buying/transmitting energy while deciding to choose a ride.

The above discussion has focused on the benefits and opportunities of an IoME future. Realising this vision requires a highly connected, trusted, and reliable information infrastructure to support accurate prediction of future energy and mobility states and enable seamless information flow across all participants within the energy and transport grids. We propose the IoME information architecture next.

**B. The IoME information architecture**

The IoME information architecture encompasses a broad range of heterogeneous devices from energy and transport
sectors that perceive the environment and transfer the data to the Service Providers (SPs) to offer personalized automated services to the users. The proposed framework consists of three layers which are summarized in Figure 3 and are described below.

The Data Generation Layer: The data generation layer consists of a broad range of heterogeneous devices that sense the environment and send the resulting data to the upper layer to be transferred to the processing layer. The data generation sources can be: i) smart grid nodes: renewable energy sources, e.g., solar panels, traditional energy producers, transmission infrastructure, EVs, and energy companies, ii) Transport nodes: including road side infrastructure (RSI), city managers, vehicle manufacturers, and vehicle service centers, and iii) IoT devices: including microclimate sensors, smart phones, and smart appliances.

The Data Communication Layer: Blockchain is employed as the underlying trusted communication layer where the participants can exchange data or control messages. Each participating node, referred to as node in the rest of the paper, is known by a changeable Public Key (PK) that introduces a level of anonymity. A single public blockchain is employed as the main chain where all participants are connected either directly or indirectly, i.e., through a gateway or controller. The participating nodes may employ private or side chains, depending on the application, to share data which in turn increases their privacy and reduces delay and overhead in managing the main chain. We refer to such chains as child chains. All the child chains are connected to the public chain where their hashes are stored periodically. The child chains may also follow a particular topology, e.g., they can be formed in a hierarchical manner (which is discussed in detail in the rest of the paper).

The Data Processing Layer: In this layer, the data produced in layer 1 is processed by the processing units that can be SPs. We enable the data to be processed based on different topologies which include: i) Cloud servers where the data is processed by a central cloud service provider, e.g., Google, ii) Edge devices where the data is processed at the edge of the network, i.e., closer to the data generation source, ii) Hierarchical structure where the data is processed in multiple layers.

III. AN EXAMPLE SCENARIO

In this section we outline the flow of interactions in the proposed framework through an example scenario as shown in the network topology in Figure 4. A public chain is managed by all the participating nodes. A private chain is run in the Virtual Power Plants (VPPs), microgrids, and the ride sharing fleet. As outlined in Section II.C, the first phase in the proposed framework is to predict the future energy demand and supply. In this example scenario, the learning is happening in a hierarchical manner.

We run through the detailed information flow within the network, as shown in Figure 5. In the energy grid, the first steps are the prediction of energy supply and demand. Recall that the proposed framework benefits from the data provided by a range of IoT devices. We assume that each smart home is equipped with a building energy manager (BEM) which potentially can be integrated with the home Internet gateway. In the first learning process, the smart home energy manager collects the data related to future energy generation and consumption which includes: solar panel, weather prediction, smart appliances, IoT devices including smart thermostat and temperature sensors, EV, and local batteries (if any). To protect the security of the communications, the data is encrypted with the PK of the BEM. Each device signs the hash of the exchanged data that protects data integrity. The participating nodes in the smart home are trusted entities and thus there is no private chain in the smart home. The BEM may receive information from third parties, e.g., weather prediction. To ensure the integrity of the data and protect against non-repudiation attack where a node denies its previous communication, the communications with external parties are stored in the public blockchain in the form of transactions.

The BEM runs the ML algorithm on the received data to predict the future energy generation and supply. The raw data of the devices is stored in a local storage along with the
outcome of the learning. Recall that sending the raw data of the devices in the smart home increases the packet and processing overhead and also risks user privacy, thus the BEM sends only the outcome of the learning algorithm to the upper layer in the hierarchy. The BEM is a member of a private chain in a microgrid where all residents of a suburb are connected. To share the outcome the BEM broadcasts an energy supply demand prediction (ESDP) transaction which is structured as follow:

\[ T_{ID}|ESDP|time\_stamp|PK|Sign \]

Where \( T_{ID} \) is the identifier of the current transaction which essentially is the hash of the transaction, ESDP is the outcome of the learning algorithm, \( time\_stamp \) refers to the time when the transaction is generated and the last two fields are PK and signature of the BEM. The manager of the private chain of the VPP collects all the ESDPs from the participating nodes in the private chain. The manager then runs the learning algorithm to predict the future energy supply demand of the VPP.

The manager of the VPP broadcasts the outcome of the learning in both the private chain and the public chain using ESDP transaction as outlined above. The energy distribution companies in the public chain run the learning algorithm after receiving data from all the participants and announce the outcome using a ESDP transaction. The energy distribution company then decides on the energy price and announces that using a energy price signal (EPS) that is structured as follow:

\[ T_{ID}|P_{T_{ID}}|Energy\_Price|Expiry \]

where \( P_{T_{ID}} \) is the ID of the previous transaction generated by the same user. The pointer to the previous transaction ID ensures that authenticity of the transaction owner. In public blockchains as the users are anonymous and there is no trust, only the participants that own the keys pairs corresponding to a transaction in the blockchain can create transaction and chain it to their previous transaction. This potentially prevents against Sybil attack where a malicious node may attempt to flood the network by sending fake transactions. \( Energy\_Price \) refers to the price of the energy and Expiry refers to the duration of time in which the price is valid for.

We next describe the information flow within the mobility grid. When an EV receives the EPS, it first checks if there is a travel scheduled during the EPS expiry time. If so, the EV checks the possibility of opportunistically maximizing user benefits by charging the vehicle in one place and discharging...
in another place. The EV must consider the required energy to travel and the time to charge/discharge:

\[
\text{Gain}(t) = \text{Gain}(\text{discharging}(L(t))) - \text{Cost}(\text{moving to } L)
\]

(1)

where \(\text{Gain}(t)\) is the overall expected gain for an EV to move to location \(L\) for discharging, \(\text{Gain}(\text{discharging}(L(t)))\) is the discharging gain and is the difference between the feed-in tariff at location \(L\) and the feed-in tariff at the vehicle’s current location, and \(\text{Cost}(\text{moving to } L)\) is the cost of relocation from the current location to \(L\).

In case there is no travel scheduled, the EV considers the best time to charge or discharge the vehicle. Similarly, EV’s used by ride sharing or other transport operators can consider energy price-driven routing decisions that consider the fleet-wide energy costs of specific transport routes, against the expected gains from energy discharging into the grid along selected routes. Both types of decisions will rely on existing mobility models \([11]\), the fusion of available mobility data \([12]\), and traffic demand prediction models \([13]\) and the SOH of this and other EV’s batteries, as inputs. At each time step, the EV’s mobility decisions will determine the charging and discharging outcomes across the transport grid, which will then feed back into the energy demand and supply respectively for the next round of energy supply and demand prediction.

IV. DISCUSSION AND CONCLUSION

The IoME vision opens up several opportunities and open research questions that we now discuss. An Internet of Mobile Energy is likely to result in monetisation and marketisation of renewable energy sources, such as sunshine. Despite the increase in penetration of rooftop solar, where in Australia for instance it has reached a penetration rate of over 25%, excess solar energy can easily reach zero or even negative price, representing a liability for energy producers. With the highly dynamic and market-driven nature of IoME, over-supply of energy in one area may be exploited by electric vehicles that opportunistically charge at times of excess supply to secure a profit by discharging later at a time of higher energy demand. Such a marketisation of renewable energy sources not only benefits mobility grid participants, but also increases benefits for energy producers that would otherwise lose the value of their excess energy.

Current electric vehicle charging and discharging technology is time-consuming, although there has been a recent trend towards fast-charging and discharging \([11]\). The vehicle must be connected to the charging station for the charging/discharging time. In recent years, charging lane roads have been developed that enable the vehicles to charge and discharge while driving which in turn impacts this delay and eliminates the need to stop in a charging station. An interesting research direction is to model this delay into routing decisions, where solutions to this problem could build on the body of knowledge in communication network routing algorithms that consider various delays in finding the optimal routes to a destination.

Another open issue is how to conduct efficient and privacy-preserving search within IoME. For instance, a search engine may be developed for real-time location of vehicles and charging stations with attractive energy prices. The search engine needs to then include attribute-based encryption that reveals sufficient information about a node without jeopardising its privacy-sensitive information. Routing within this network can be anonymous, for instance using our anonymous backbone routing protocol \([14]\).

The transportation industry is also expecting disruption by the penetration of autonomous self-driving vehicles that employ a broad range of sensors installed in the vehicle along with decision making algorithms to enable self-driving feature and eliminate the need for human interactions. The vehicles are normally parked in a location, e.g., when the owner is at work. During such time, autonomous vehicles can transport energy within IoME which in turn increases the benefits of the users.

Transferring energy to rural areas is highly costly for energy managers particularly in remote areas due to significant cost for transmission infrastructure. Additionally, in case of disaster, e.g., flood, these areas may get disconnected from the grid. The seamless transportation of energy offered by IoME enables the participants to transfer energy produced by DES and thus prevents energy shortage or disconnection in such areas.

An Internet of Mobile Energy will support greater convergence and seamless interaction across the transport and power sectors. IoME benefits from the maturation of technologies in both sectors and to the availability information technologies such as IoT, blockchain, and machine learning. While realising IoME involves several open challenges that we have outlined in this paper, an Internet of Mobile Energy is expected to deliver significant benefits for innovation, efficiency in both transport and power sectors, and welfare to end users across both sectors.

REFERENCES

[1] https://www.fastcompany.com/90347555/this-electric-road-charges-your-car-while-you-drive
[2] Bloinsky, M., Nagarajan, A., Ghosh, S., McKenna, K., Veda, S., & Kroposki, B. (2019). Potential Impacts of Transportation and Building Electrification on the Grid: A Review of Electrification Projections and Their Effects on Grid Infrastructure, Operation, and Planning. Current Sustainable/Renewable Energy Reports, 6(4), 169-176.
[3] Morrissey, P., Weldon, P., & OMahony, M. (2016). Future standard and fast charging infrastructure planning: An analysis of electric vehicle charging behaviour. Energy Policy, 89, 257-270.
[4] A. Dorri, S. Kanhere, R. Jurdak, P. Gauravaram, LSB: A Lightweight Scalable BlockChain for IoT Security and Anonymity, Journal of Parallel and Distributed Computing, 134: 180-197, December, 2019.
[5] Divya, M., and Nagaveni B. Biradar. "IOTA-next generation block chain." International Journal Of Engineering And Computer Science 7, no. 04 (2018): 23823-23826.
[6] W. Yao, J. Zhao, F. Wen, Y. Xue, and G. Ledwich, A hierarchical decomposition approach for coordinated dispatch of plug-in electric vehicles, IEEE Transactions on Power Systems, vol. 28, no. 3, pp. 2768-2778, 2013.
[7] F. Luo, G. Ranzi, S. Wang, and Z.Y. Dong, Hierarchical energy management system for home microgrids, IEEE Transactions on Smart Grid, vol. 10, no. 5, pp. 5536-5546, 2019.
[8] E. Reithani, S. Sepusi, L.R. Roose, and M. Matsuura, Energy management at the distribution grid using a battery energy storage system (BESS), International Journal of Electrical Power and Energy Systems, vol. 77, pp. 337-344, 2016.
[9] L. Li, K. Ota, and M. Dong, When weather matters: IoT-based electrical load forecasting for smart grid, IEEE Communications Magazine, vol. 55, no. 10, pp. 46-51, 2017.

[10] A.Y. Saber and T. Khandelwal, IoT based online load forecasting, in Proc. 2017 Ninth Annual IEEE Green Technologies Conference, Denver, Mar. 2017.

[11] Noulas A, Scellato S, Lambiotte R, Pontil M, Mascolo C. A tale of many cities: universal patterns in human urban mobility. PLoS ONE. 2012;7(5):e37027. pmid:22666339

[12] Liebig J, Jansen C, Paini D, Gardner L, Jurdak R (2019) A global model for predicting the arrival of imported dengue infections. PLOS ONE 14(12): e0225193.

[13] Yao, Huaxiu, Fei Wu, Jintao Ke, Xianfeng Tang, Yitian Jia, Siyu Lu, Pinghua Gong, Jieping Ye, and Zhenhui Li. “Deep multi-view spatial-temporal network for taxi demand prediction.” In Thirty-Second AAAI Conference on Artificial Intelligence. 2018.

[14] A. Dorri, F. Luo, S. S. Kanhere, R. Jurdak, Z. Y. Dong, SPB: A Secure Private Blockchain-based Solution for Distributed Energy Trading, IEEE Communications Magazine, vol. 57, no. 7, pp. 120-126, July 2019.