RESEARCH ARTICLE OPEN ACCESS

Smart Charging Using Footstep Power Generation System

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ABSTRACT

One of the cornerstones to powering a carbon-neutral world by 2050 is greater direct electricity of end-use industries with a bigger mix of renewables. The integration of renewable energy with power systems, in contrast to traditional power plants, is fraught with difficulty. Decision-makers now rely heavily on scenario-based probabilistic forecasting models. To provide accurate scenario-based probabilistic predictions, which are essential to meet the emerging difficulties in power systems applications, this study introduces the power systems forecasting professionals to a novel deep learning approach called normalization flows.The benefit of this method is that it uses likelihood maximization to directly learn the stochastic multimodal distribution of the underlying mechanism. We show that our technique is competitive with other cutting-edge deep learning generative models, including adversarial networks and variationally autoencoders, through thorough empirical assessments utilizing the available data of the World Energy Forecasting Competition 2014. By considering the case study of an electricity retailer and employing a number of complementing criteria, the models that provide weather-based windy, solar power, and load situations are correctly evaluated in terms of forecast value.

The mathematical experiments are straightforward and simple to duplicate. As a result, we anticipate that it will motivate other forecasting experts to experiment with and make use of normalizing flows in power systems like electricity market bidding, scheduling power systems with a high penetration of renewable energy sources, power management of virtual power plans or micro - grids, and unit commitment.

Keywords: Deep Learning, restoring, Forecasting, Time Series, Adversarial Network, Auto Encoders.

I. INTRODUCTION

Solar inverters are machinery that convert solar energy into either AC or DC power. A grid operator may purchase this electricity, store it in a battery or other type of storage device, or use it right away to satisfy the electrical load. To fulfil the load, power from the grid or battery can also pass via the inverter. In Figure 1, we can observe these power flows. This technology can provide energy supplies at the home level while raising the payload capacity (that is, the proportion of average to peak demand) at the grid level. This technology will play a crucial role in decreasing carbon emissions globally to fulfil the goals of the Paris Climate Agreement.Australian company Redback Technologies produces intelligent solar inverters. Smart inverters, as opposed to conventional inverters, may send and receive signals fast and can share precise data with the owner, the utility, and other stakeholders. These inverters can monitor, regulate, and store solar energy for a residence. Appliances can be connected as "AC loads" or "Backup loads" inside a house. In the absence of grid power, backup load can be powered by the energy conversion system and solar energy. The average instantaneous value of the home's total load is less than 10 kW.

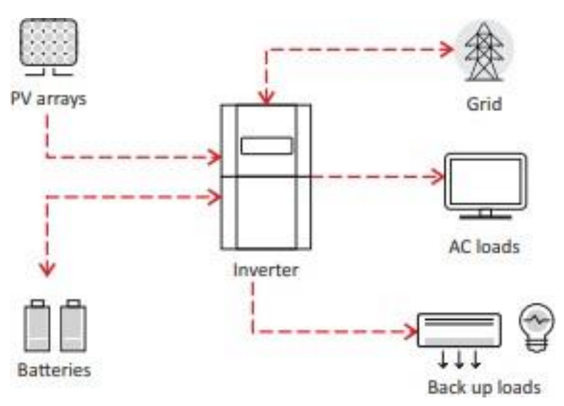

Figure No. 1 - Schematic of an inverter with connected grid, battery, and electrical loads

The typical load in most households is 300 W or more. PV stands for photovoltaic power, and the solar panels connected to the inverter have a 5-kW rating. If the inverter were in Australia and the solar panels were 5 kW, the average daily output would be between 17.5 kWh and 25 kWh (Hobart to Alice Springs) ([5]). To prevent negative impacts or battery failure, the batteries connected to the inverters have a state of state value that must be maintained within a certain range of values (for example, 20%–100%). The data on the load, PV, state - of - charge, and overall health of the batteries is kept in one place and is updated often.This makes it possible for consumers to control and monitor their energy requirements with a smartphone app. Users have the option of seeing both current values and cumulative historical values. You may also see the PV and load projections. The user can also view predicted costs if tariffs are known. Customers may also pick their inverter panels size and type, as well as their battery type (such as lithium ion or zinc bromide). The three operating modes for the inverter are automatic (described in more detail below), charge mode, and discharging mode with a predetermined rate. To establish a battery charging or flow velocity or to switch the operation mode to automated, orders may be sent from a central point to the inverter.

You can do this around once per minute. The secret to the savings mentioned in section I-A lies in this. An objective function, such as the cost of power over the next 24 hours or the peak demand over the following month, can be reduced by creating a battery command schedule. The inverter is independent of the battery type, but for optimal placement, it should be aware of the roundtrip effectiveness of the battery and inverter system as well as the battery's level of charge when optimization should take place. Only certain manufacturers of lithium-ion batteries presently have access to and are aware of these efficiency estimations and state of charge numbers (e.g. Pylon, LG).

The many categories of probabilistic predictions include quantile, density, scenarios, and prediction interval forecasts [4]. This study focuses on affected by the context, a well-liked probabilistic forecasting technique to account for load, photovoltaic (PV), and wind generation variability. It entails creating lists of potential load or power realities for one or more places.

The two main categories of forecasting approaches are statistical models and machine learning methods. On only one hand, statistical methods are easier to understand than machine learning methods, sometimes known as "black-box models." However, compared to statistical procedures, they are typically more reliable, approachable, and effective in resolving the quasi in the data. The following section includes a few examples of statistical techniques. More references may be found in **Mashlakov et al. [7] and Khoshrou and Pauwels [6].**

II. LITERATURE REVIEW

Several publications on various methods for scheduling batteries with a solar inverter have been written by **Nottrott, Kleissl, and Washom ([15]),** as well as **Hanna, Kleissl, Nottrott, and Ferry ([**10]). They provided the following descriptions of the OFF ON, RT, and OPT methodologies.

ON/OFF Approach, this method involves doing one daily fully charged battery cycle on the battery while it is 80 percent discharged. During off-peak hours, a constant charging rate is used, while during peak hours, a constant flow velocity is used. With a known load, such as an industrial or commercial load, this strategy is simple to implement, but not for a residential load.

RT Approach,in this method, the battery is fully charged during off-peak hours and drained in real time to meet the customer's actual net load. The automated technique detailed in this paper's discharging process is the same.

OPT Approach, Forecasts for PV and load are used in this method. Time-of-use rates are not employed because there are no costs involved with purchasing or selling power from the grid under this approach. The method is like the one employed in this paper since it improves using a linear system. In contrast, the function that must be reduced is the total of the net PV and battery systems output power levels that are below the anticipated customer load.

One of the most well-known deep learning methods used in energy forecasting applications is recurrent neural networks (RNNs). In the area of forecasting short-term household load, **Shi et al.** [14] present a new pooling-based deep recurrent neural network. It performs better than statistical techniques like the conventional RNN and the autoregressive integrated moving average. In **Dumas et al.,** a customized forecasting tool by the name of encoder is used. [13]

projections for intraday multi-output PV quantiles. **Hewamalage et al [18]**.'s guidelines and best practices for forecasting practitioners are based on a thorough empirical investigation using an open-source software architecture of current RNN architectures. Bidirectional long short-term memory (BLSTM) design was implemented in the continuum by **Toubeau et al.** [19]. To produce scenarios, it is trained using regression model and integrated with a copula-based methodology. This method's forecast quality and value are compared to those of other models in a scenario-based randomized optimization case study. Finally, **Salinas et al.** [10] used a variety of real-world datasets to train an autoregressive recurrent neural network. With minimal to no hyper-parameter adjustment, it generates precise probabilistic forecasts.

III. RELATED WORK

In terms of computing speed, variety, and architectural limitations, they all trade off. Two papers are suggested to gain a deeper understanding of this area. (1) **Bond-Taylor et al** thorough analysis of current generative modelling trends [11]. To forecasting professionals, it delivers generative models inside a solitary, unified statistical framework. (2) **Ruthotto and Haber's** [12] comprehensive comparison of normalizing flows, variationally auto - encoders, and generating adversarial networks. It uses numerical computer vision exercises to explain the benefits and drawbacks of each technique. We will concentrate on generative model applications in power systems in the sections that follow.

In a group of methods known as deep generative modelling, deep neural networks are trained to simulate the distribution of the data. Large open-access dataset's emergence and advancements in both generative models and generic deep learning architectures have allowed for a growing interest in this area in recent years. Energy-based models, variationally approaches can be distinguished, generative adversarial networks, adapted, normalizing flows, and several hybrid techniques are just a few of the methods that may be used.In terms of computing speed, variety, and architectural limitations, they all trade off. Two papers are suggested to gain a deeper understanding of this area. (1) **Bond-Taylor et** cetera analysis of current generative modelling trends [11]. To forecasting professionals, it delivers generative models inside a solitary, unified statistical framework. (2) The extensive comparison of generative adversarial networks, variational autoencoders, and normalization flows offered by **Ruthotto and Haber** [12].It uses numerical computer vision exercises to explain the benefits and drawbacks of each technique. We will concentrate on generative model applications in power systems in the sections that follow.

Deep generative models, such as Variationally Autoencoders (VAEs) [13] and Generative Adversarial Networks (GANs) [14], directly learn a generative process of the data, in contrast to statistical techniques. They have shown to be effective in a variety of applications, especially those involving power systems, to produce precise probabilistic predictions. Both produce probabilistic predictions in the form of **Monte Carlo** samples, from which it is possible to derive consistent quantile estimates for each sub-range in the prediction horizon. As a result, they are immune to the problem presented by **Ordiano et al.** [15]

IV. ARCHITECTURE AND MODEL

The object-oriented, modular architecture used by ACN-Sim is seen in Fig. 2. It is simpler to expand the simulator for additional use cases thanks to this architecture, which as closely simulates physical systems as feasible. A basic class that may be expanded to simulate new behavior or add functionality is represented by each box in Fig. 2. Although ACN-Sim comes with many models of each element, customers can adapt the simulator to their own requirements. We invite researchers to return to the project with enhancements that can be used by others.

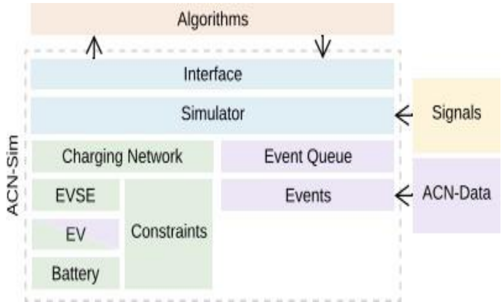

Figure No. 2 - Signals, Algorithms, and ACN-Data are connected sub-modules that make up the architecture of ACN-Sim. Keep in mind that EV models both the actual vehicle and session data, such as the requested energy and departure time.

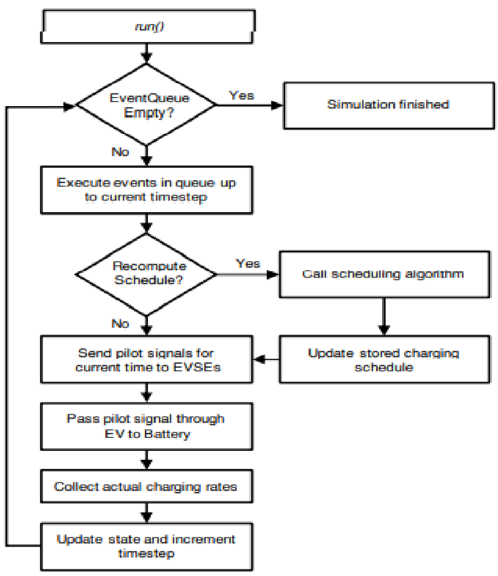

Figure No. 3 - Flowchart outlining the run () function of the simulator. A single iteration of this loop takes place throughout each timestep. When the final event in the Event Queue is processed, the simulation ends, at which point the user can evaluate the outcomes.

4.1 : Simulator

Any ACN-Sim simulation starts with a Simulator object as its foundation. The physical components in the simulated environment are represented by models in this simulator, and a queue of events determines when system operations take place. A discrete-time, occurrence simulation model serves as the foundation for ACN Sim. Figure 3 explains how it works. The Simulator records pertinent information during a simulation for further study, including the event history, EV history, time series again for pilot signal, and the charging current for each EVSE.

4.2 : Charging Network

Electrical Infrastructure: ACN-Sim models the power grid of the battery charger, including EVSEs, using the Charging Network class. cables, switch panels, transformers, etc. Several EVSE objects and a number of restrictions are present in each Charging Network instance.

By restricting the current flowing through each bottleneck element in the network, we simulate limitations. It is sufficient to model just restrictions on current magnitudes because charging networks are radial networks because electrical standards define ampacity limitations that maintain voltages within requirements. Kirchhoff's Current Law allows us to describe these restrictions in terms of bytes.

$$|I_{j\,(t)}| = |\sum_{i=1}^{N} A_{ij} r_i(t) e^{j\phi_i}| \leq R_j, \in t$$

where N is the maximum number of EVSEs in the network, ri(t) is the recharging power of EVSE I at time t, & T is the collection of all time - steps in the simulation. Ij (t) is the power through the bottleneck. The network connection of EVSE I will determine the parameter I which is the phase difference of the present phasor. For the sake of simplicity, we'll assume that I is fixed and the network's voltages are nominal. Circuit analysis may be used to find Aij, as illustrated in [4] for a portion of the Caltech ACN.

4.3 : Random Space Assignment

The EVSEs are always assigned to a different EV, and no two EVs ever are allocated to the exact same EVSE at the same time, according to Charging Network. When a workload from ACN-Data is applied to the relevant network model, this is true. Allowing for non-deterministic space assignments, however, might be beneficial in some circumstances, such as when generating occurrences from a statistical model or matching a real workload to a fresh network configuration. This is achieved by ACN Sim using the Stochastic Network class (which is a subclass of Charging Network). With this network topology, when EVs arrive, they are not allocated to a specified station id, but rather to a randomly open EVSE for a project. Stochastic Network also features a waiting list for EVs that arrive when all EVSEs are in use since it is conceivable for there to be no EVSEs available when a new EV arrives. The first EV in the line is put in its place when an EV exits the system. By default, we believe that drivers' departure times are not affected by the presence of EVs in the line waiting. However, as soon as drivers have finished charging, they switch places with the first EV in the line using the early departure option. This is a normal procedure in lots of workplaces whose EV drivers outnumber EVSEs.

4.4 : Included Side Model:

Users are free to create their own charge networks, although ACN-Sim has tools for creating network models that correspond to the actual layout of the three locations that are now part of ACN-Data (Caltech, JPL, and Office001). Additionally, users may easily construct straightforward single-phase and three-phase networks using the auto ACN function by supplying only a list of station ids and a transformer capacity. It is expected that the inverter is the sole source of restrictions in these auto acn networks. Both Charging Network and Random Network, which may be configured as a parameter, are compatible with all these functions.

4.5 : EVSE

Electric car supply equipment, or EVSEs, are the outlets that EVs connect into to charge. The maximum amount of current that the EV is permitted to draw from the EVSE is sent by the EVSE through a pilot signal to the EV's on-board charger. This pilot's level of detail depends on the specific EVSE. While some EVSEs allow discrete set-points, others simply give continuous control. The J1772 standard also states that no pilot signals are permitted between 0 and 6 A [20]. The extra restrictions put forth by EVSEs without control scheme are often ignored in current research [1]. It is not simple to include these limitations yet doing so is necessary for effective algorithms.

4.6 : EV

The EV object includes pertinent data for a single recharging session, including requested energy, arrival time, time of departure, and predicted departure time. The actual departure time can be different from the projected time. The delivery of the required energy in the allocated time may also be impossible owing to limitations on the maximum charging rate, backed-up systems, or inadequate battery capacity. This enables ACN-Sim to simulate the scenario in which user inputs or forecasts are incorrect, which occurs often in practice [5].

4.7 : Battery

The majority of EV charging research use an ideal battery model, where EVs are presumptively expected to follow the provided pilot signal precisely. Though, we see that an EV's charging rate is frequently strictly lower than the pilot signal and starts to decline as the battery gets closer to being fully charged [1], [4]. The battery may need to be charged for a longer period as a result, underutilizing the infrastructure's capacity.The vehicle's battery and battery management system are collaboratively modelled by ACN-Sim. The pilot signal, the vehicle's on-board charger, the battery's level of charge, and other external conditions all affect how quickly the battery charges. Currently, ACN-Sim offers two battery types.

All other battery models are based on the Battery class, an idealized model. In this idealized model, the battery's real charging rate, r(t), is represented by

$$r\widehat{(t)} = min\{r(t), r, e(t)\}$$

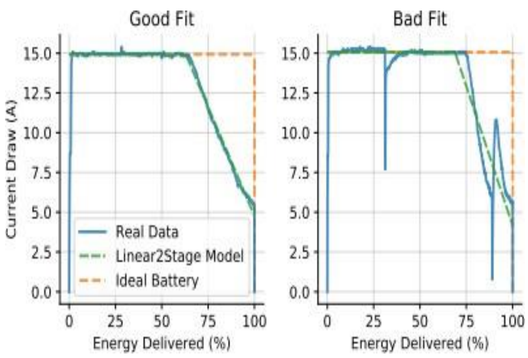

Figure No. 4:When the pilot signal is not binding, a comparison of the Linear2Stage and idealized Battery models with an actual charging curve obtained from two different users of the Caltech ACN is made. We can see that in the first scenario, the Linear2Stage model with the proper parameters accurately predicts the battery behaviors, but in the second situation, the Linear2Stage model fails to account for some dynamics in the joint battery/battery manager system, specifically the double-tail behavior (which is recurring for this user).

where e(t) is the discrepancy between the battery's capacity and the energy it has stored at time t in aperids, r(t) is the pilot signal sent to the battery, r is the on-board charger's maximum charging rate, and r is the pilot signal. All rates are positive since battery discharge is not taken into account.

An extension of Battery called Linear2StageBattery simulates the roughly piecewise linear charging method employed by lithium-ion batteries. Bulk charging, the first step, generally lasts from 0% to between 70 and 90% state-of-charge. Considering no modifications to the pilot throughout this phase, the current draw is essentially constant. The battery voltage is maintained constant throughout the second stage, known as absorption, while the charging current declines roughly linearly. The Linear2StageBattery's real charging rate is provided by

$$\hat{r}(t) := \begin{cases} \min\{r(t),\ \bar{r},\ \hat{e}(t)\} & \text{if } \mathtt{SoC} \leq \mathtt{th} \\ \min\left\{(1-\mathtt{SoC})\,\frac{\bar{r}}{1-\mathtt{th}},\ r(t)\right\} & \text{otherwise} \end{cases}$$

where th denotes the change from the bulk stage to the absorbing stage of the charging process and SoC denotes the battery's state-of-charge. Figure 4 illustrates the differences between these two models for two charging patterns collected from ACN-Data. The piecewise linear model, while not perfect, is often found to be a decent approximation.

V. CHARGING ALGORITHM

5.1 : Interface

We offer an interface that abstracts away the infrastructure, whether it be simulated or real, allowing us to utilize the same algorithm implementation with both ACN-Sim and ACN-Live. This increases the flexibility of algorithm implementations. Consequently, algorithms may be properly tested.Prior to being utilized with actual hardware, they are ACN-Sim tested.

5.2 : Defining an Algorithm

Users of ACN-Sim just need to specify the schedule () method and extend the Base Algorithm class to define an algorithm. This function accepts a list of active sessions, which denotes a plugged-in electric vehicle whose energy requirements have not yet been satisfied and returns a charging plan for each. The validity of each entry in the schedule is for a single timestep starting now. The Interface class gives algorithms access to extra details about the simulation, such as the current time - step, infrastructure restrictions, and permitted pilot signals for each EVSE.

5.3 : Included Algorithm

Many widely used online task scheduling that may be used as benchmarks are included with CN-Sim.

- Uncontrolled Charging: Today, most charging solutions do not handle charging. Each EV charges at the fastest possible rate when uncontrolled charging is used. Infrastructure restrictions are not considered by this approach.
- Round Robin: A straightforward method called Round Robin (RR) aims to distribute the available charging capacity across all active EVs evenly. All the active EVs are put into a queue. It determines if it is possible to increase each EV's charging rate by one unit. If so, it raises the rate and swaps out the EV at the back of the line. If not, the system does not put the EV back in line because its charging rate is fixed. This goes on until there are no more EVs in the line.
- Sorting Based Algorithm:Due to their simplicity, sorting-based algorithms are frequently employed in various deadline scheduling problems, such as work scheduling in servers [14].These algorithms are First-Come First-Served (FCFS), Last-Come First-Served (LCFS), Earliest-Deadline First (EDF), Longest Remain Processing Time (LRPT), and Least-Laxity First, among others, that are included in ACN-Sim (LLF). These algorithms operate by selecting the active EVs according to the specified measure before processing them sequentially. Given that the allocations to all earlier EVs are established, each EV is given its maximum practicable charging rate. This procedure keeps on until all EVs have been handled.
- Model Predictive Control:Model predictive control is a key component of several solutions to the EV scheduling challenge (MPC). Based on CVXPY [26], [27], the ada charge package, which is offered at [25], makes it simple to employ these algorithms with ACN-Sim. With the help of this library, users may quickly construct new goal functions and restrictions or select from a list of pre-existing ones. [4] provides a general description of the framework for various MPC algorithms.

VI. USE CASES

Numerous research issues have been investigated using ACN-Sim. Examples given in this area include assessing (1) potential infrastructure fixes, (2) the impact of imbalance on oversubscribed infrastructure, (3) time-series of EV charging profiles, and (4) the impact of extensive EV charging on a distribution feeder. ACN-Sim has also been applied in the design of dynamic pricing schemes and cost-effective scheduling [13], in the training of reinforcement learning agents for EV charging systems [12], and in the analysis of the impact of non-ideal batteries and EVSE pilot quantization on model predictive control and baseline algorithms [10]. The source code for each of the case studies described here can be found at [11].

6.1: System Planning

We show how the simulator can help with system planning and design in this part. We consider a site host who wants to set up an EV charging station in an office complex. According to the host, the system will charge about 100 EVs every day. The options for satisfying this need are listed in Table I. Every one of these choices comes with trade-offs.

ACN-Sim may be used to direct this website host. We anticipate that the office's consumption will be comparable to JPL's. As a result, as stated in [5], we train a Gaussian Mixture Model using data gathered from JPL's weekday usage. We presume that the website won't permit use on the weekends. Then, assuming 100 arrivals on weekdays and 0 on weekends, we utilise ACN-GaussianMixtureEvents Sim's tool to generate a queue of events from this generative model. Additionally, we simulate the charging networks that are discussed in each plan. We employ the StocasticNetwork, which distributes EVs to EVSEs at random when they arrive, since EVs are created. We apply the built-in Uncontrolled charge algorithm to ideas 1, 2, and 3.We take into consideration an MPC-based cost-minimization method for proposal 4. We compare the scenarios based on four factors: 1) the amount of transformer capacity needed, 2) the proportion of the total amount of energy requested that was delivered, 3) the number of times drivers must switch spots to make room for others to start charging after they finish, and 4) the able to operate cost of the system based on the warmer months rates from the tariff schedule included in ACN-Sim, the scetouev 4 march 2019 tariff schedule. With mean findings provided in Table I, we repeat these tests for 10 months of collected data. Keep in mind that for each statistic, the standard variation between months was around 3.5% in each case.

EVSEs (#)	EVSE Type	Alg	Transformer Capacity	Swaps (#/month)	Demand Met	Cost ($/kWh)
102	Level 1	Unctrl	200	0	75.4%	0.278
102	Level 2	Unctrl	685	0	99.9%	0.351
30	Level 2	Unctrl	200	1,103.5	99.6%	0.256
102	Level 2	MPC	200	0	99.8%	0.234

Table No. 1 - INFRASTRUCTURE SOLUTION EVALUATION (100 EV / DAY)

EVSEs (#)	EVSE Type	Alg	Transformer Capacity	Swaps (#/month)	Demand Met	Cost ($/kWh)
102	Level 1	Unctrl	200	1,174.5	73.2%	0.244
102	Level 2	Unctrl	680	1,081.5	99.8%	0.327
30	Level 2	Unctrl	200	2,973.9	91.6%	0.233
102	Level 2	MPC	200	1,441.9	87.1%	0.223
201	Level 2	MPC	200	0	98.4%	0.227

Table No.2 - INFRASTRUCTURE SOLUTION EVALUATION (200 EV / DAY)

In this instance, the smart charging system with model predictive control offers unmistakable benefits in terms of operational expenses, user happiness, and capital cost (only requiring a 200-kW transformer) (having the lowest cost per kWh). This demonstrates the actual demand for intelligent charging methods.

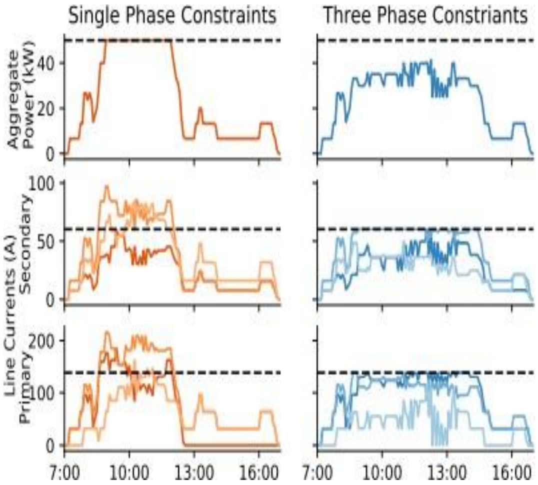

Figure No. 5 - By using single-phase and three-phase LLF algorithms on the Caltech ACN with a 50-kW transformer capacity, the total power demand and line currents at the primary and secondary side of the transformer. Each phase is indicated by shading in the lower plots, and the black dotted line designates the power/current limit. The experiment employs a 5-minute timestep and data from the Caltech ACN on March 5, 2019.

As EV usage rises, the advantages of smart charging methods become more apparent, and charging infrastructure must develop in step. We consider how the system would expand to 200 charging sessions per day in this case. Table II presents the findings. It seems sense that when demand rises, the systems built for 100 EVs a day will need to do far more swaps, and vice versa. For the smart charging (MPC) instance, the same is true. However, the smart charging strategy enables us to add more EVSEs without raising the transformer capacity, whereas multiplying the number of EVSEs in conventional uncontrolled charging systems would require a matching scaling of the transformer capacity to assure safety.We can add a second EVSE using the same wire next to each of the originals to provide scalability. The charging algorithm is then used to make sure the cable's capacity is not exceeded. As a result, expanding the number of EVSEs is simple without expanding transformer or connectivity capacity.

It's interesting to note that for all systems, the effective cost per kWh lowers as the number of EVs the system serves rises. This demonstrates the scale economics that are connected to demand charge. By spreading the demand fee over more supplied energy with increased consumption, it is feasible to lower the cost per kWh. Because of the necessity to charge consumers during more costly TOU periods, the fall in demand charge is larger than the increase in energy price, resulting in a net decrease in per-unit expenses.

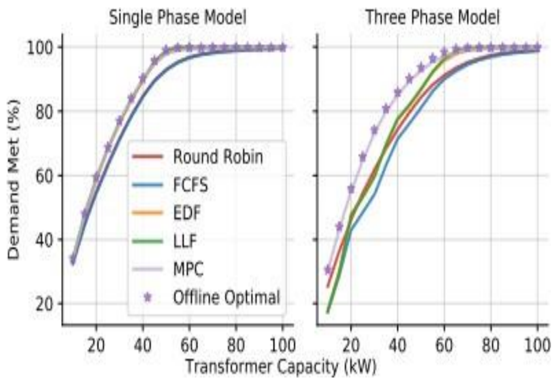

Figure No. 6 - Comparison of energy delivery % as a function of single-phase (left) and three-phase (right) system transformer capacities The offline optimum, which is an upper bound based on, is represented by stars. complete knowledge of the future. The simulation lasts from September 1 to October. 1, 2018, with a 5-minute timestep. We obtain actual charging sessions through the ACNSim's connection with ACN-Data in order to create events. Using the optimal battery model, Caltech ACN. In addition, we make advantage of the Use the optimum EVSEs from the Caltech ACN charging network model and its optional transformer cap parameter to set a capacity cap on the infrastructure.

Three-phase infrastructure that is unbalanced can also affect how we rate algorithms. How well EV charging algorithms meet user energy demands when infrastructure restrictions are binding is a crucial assessment indicator. Based on the actual charging workload of the Caltech ACN from September 2018, we use this metric to assess six algorithms over a range of potential transformer capacities. We undertake this experiment using single-phase and three-phase models, as shown in Fig. 6, to illustrate the impact of infrastructure models. Here, we can see that in the case of a single phase, EDF, LLF, and MPC all perform almost ideally, outperforming Round Robin and FCFS by up to 8.6%.The subplot on the right, however, offers a different tale. Here, we can observe that while EDF and LLF both perform poorly, the MPC algorithm can equal the offline optimum performance as previously. In spite of having less knowledge of the workload, Round Robin performs better in the severely confined environment than EDF and LLF. We relate these findings to the significance of phase-balancing in three-phase systems, which has hitherto received insufficient attention in the literature on controlled charging.

VII. CONCLUSION

Here, we introduce ACN-Sim, a data-driven simulation tool created to support the creation of useful online scheduling algorithms for EV charging. Researchers' software engineering workload is greatly lightened by this tool, which also exposes them to real-world practical problems in charging systems. Additionally, ACN-Sim makes it simpler for researchers to publish the experiment code they create, enhancing community code reuse and transparency. The Adaptive Charging Network Research Portal, a wider collection of resources that includes a database of actual charging sessions and a framework for field testing algorithms, also connects with ACN-Sim. ACN-Sim will keep expanding to satisfy community demands, including additional models of system parts, and charging networks.

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