ACM e-Energy 2022

EVSense: A Robust and Scalable Approach to Non-Intrusive EV Charging Detection

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Agenda

Background: Why We Need EV Charging Detection

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The **electric vehicle (EV) market is booming**: The number of EVs has grown dramatically, with a CAGR of 21.7% [4].

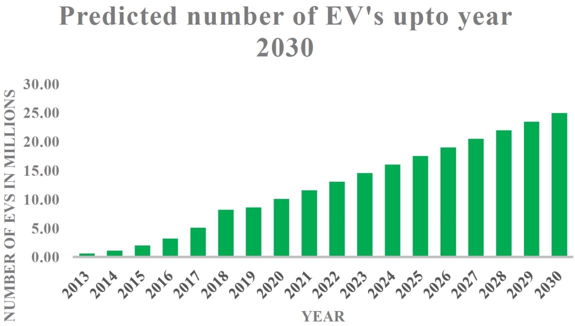

Figure 1: Trend of electric vehicles (EVs) in the global market [4].

Figure 2: Household EV charging pile.

In addition to EV charging stations which have relatively mature power planning and supply, the growth in the number of **household charging piles** needs our attention.

Background: Why We Need EV Charging Detection

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Challenges and requirements for grid:

- **Flexibility:** Enormous distributed energy storage in the EV fleet. Highly dynamic aggregate power demand of the EV charging.
- **Stability:** EV charging process can introduce harmful harmonic components into the power distribution network [17].

To better support power planning and operation, grid operators will need to know: **When do EVs charge, for how long, and at what power rates?**

⬇

In this paper, The goal of our work is to cost-effectively supply these answers at scale.

Background: NILM Task of EV Charging Detection

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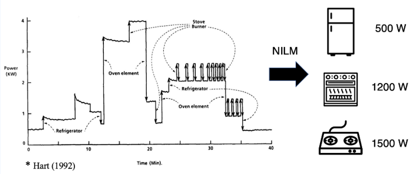
For the grid operators, they usually only have access to the readings from the main household meter. It's impossible to install a specific detector in every residents house. **(Non-intrusive way is required)**

Non-intrusive load monitoring (NILM) [19, 14, 6]

Identifying all appliances and their energy consumption from the aggregated load curve.



Our paper focus on the NILM of EV charging in residential settings.

Consider the household EV charging pile as an appliance, we use NILM to detect EV charging.

Related Work: EV Charging Detection with NILM

- **Rule-based Approaches:**
  1. 2011, *"An improved non-intrusive load monitoring method for recognition of electric vehicle battery charging load"* *Steady-state model* to detect EV charging events by matching and analyze the EV charging load profile from mains signal. [17].
  2. 2014, *"Training-free non-intrusive load monitoring of electric vehicle charging with low sampling rate"* added thresholding for aggregated signals and filtering for spikes/noise [18] to estimate the charge consumption. ***(State-of-art rule-based approach)***
- **Learning-based Approaches:**
  1. *The factorial hidden Markov model* (FHMM) for NILM [11, 5, 20].
  2. 2018, *Auto-encoder model* to identify EV charging [15].
  3. 2020, *Deep generative model with an embedded HMM model* and applied neural networks to approximate posterior distributions of HMM model's hidden units.[16].

Robustness? (simulated data, selected scenarios.)
Low latency? (no online algorithms, long detection-time delay.)
Scalability? (all above approaches were neither considered scalability in designs nor evaluated in experiments.)

Our Contributions

1. We propose **EVSense**, a DNN-based approach to non-intrusive EV charging detection. It can achieve robust EV detection in NILM way.
2. We apply a **federated transfer learning (FTL)** framework to address the **scalability** concern of model deployment. It allows **large-scale deployment** of EVSense even in resource-limited edge devices.
3. Using experiments on both **real-world** and **synthetic datasets**, we demonstrate that EVSense can achieve **higher precision** and more **robust** charging detection than existing approaches.

Problem Definition

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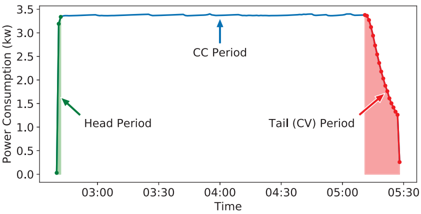
Non-Intrusive EV Charging Detection:

With the supervised information of **x** and **y**, we aim to train a model $\mathcal{F}$ for the corresponding resident, such that for any input aggregate power reading $\hat{x}$ in a (short) period, the model outputs the EV charging state $\hat{y}$ in the same period, i.e., $\mathcal{F}(\hat{x}) \rightarrow \hat{y}$.



How to **accurately** and **timely** get the EV charging event state is equally challenging and practically meaningful compared to load decomposition.

Denote N consecutive power readings at a certain sampling rate by the following vector:

$$\mathbf{x} = [x_1, x_2, \cdots, x_N], \tag{1}$$

where $x_n \in \mathbb{R}_{\geq 0}, 1 \leq n \leq N$, represents the aggregated power reading at time slot n. The vector to indicate the EV charging states:

$$\mathbf{y} = [y_1, y_2, \cdots, y_N], \tag{2}$$

where $y_n \in \{0, 1\}, 1 \leq n \leq N$, denotes the charging state at time slot n, with 1 denoting EV charging is "ON" and 0 denoting "OFF".

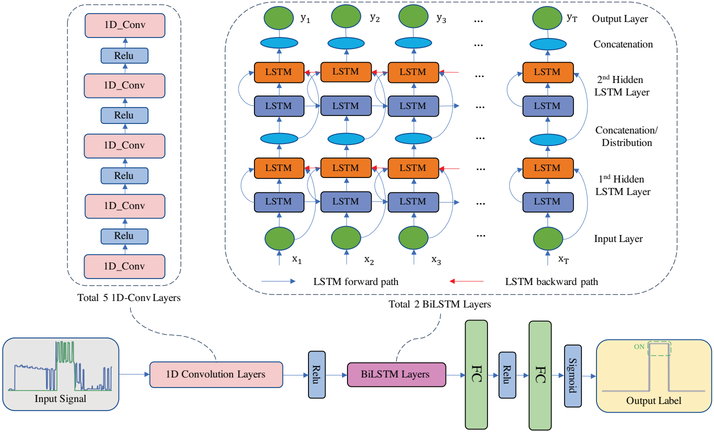


Figure 3: Network structure of EVSense[1] model, including the convolution layers, BiLSTM layers and fully connection layers.

[1] Paper code is available on Github: `https://github.com/MathAdventurer/EVSense`

Model Design

Model Structure

- **1D-Conv layers:**
  1. Design for input length = 20:
     (conv1): in_channels=1, out_channels=30, kernel_size=3, stride=1
     (conv2): in_channels=30, out_channels=30, kernel_size=5, stride=1
     (conv3): in_channels=30, out_channels=40, kernel_size=6, stride=1
     (conv4): in_channels=40, out_channels=50, kernel_size=5, stride=1
     (conv5): in_channels=50, out_channels=50, kernel_size=5, stride=1
  2. Design for input length = 10:
     (conv1): in_channels=1, out_channels=30, kernel_size=2, stride=1
     (conv2): in_channels=30, out_channels=30, kernel_size=3, stride=1
     (conv3): in_channels=30, out_channels=40, kernel_size=3, stride=1
     (conv4): in_channels=40, out_channels=50, kernel_size=4, stride=1
     (conv5): in_channels=50, out_channels=50, kernel_size=2, stride=1
- **Bi-LSTM layers:** input_size=50, hidden_size=50, num_layers=2
- **Fully connection layers:**
  (fc1): in_features=100, out_features=1024
  (fc2): in_features=1024, out_features=1
- **Activation function:** Relu, Sigmoid(Only for the output layer)

Loss Function

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As EV charging sessions are very sparse over time, traditional metrics (like accuracy) and corresponding loss functions (like cross-entropy loss) are ineffective.

Dice similarity coefficient (DSC).

$$DSC = \frac{2TP}{2TP + FP + FN}. \tag{3}$$

Binary Dice loss can be derived as the loss function for training EVSense:

$$\mathcal{L}_{\text{binDice}} = 1 - 2\frac{\sum_{n=1}^{N} \hat{y}_n y_n}{\sum_{n=1}^{N} (\hat{y}_n + y_n)}, \tag{4}$$

where y_n and $\hat{y}_n$ denote the ground-truth and predicted EV charging states, respectively, and N is the total number of time slots. In the binary event state classification, Eq. (4) is **differentiable** and thus can be directly applied for training.

Model Enhancement

i) Refined Input Labeling

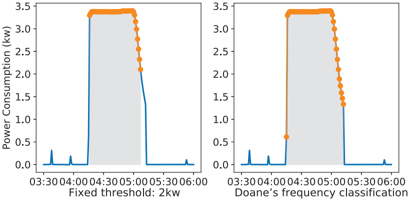


Figure 4: Comparison of EV charging event labeling methods: fixed power threshold (left) vs. statistic feature based method (right).

Using Doane's frequency classification algorithm [2] instead of fixed threshold for labeling data. **Get more complete charging events.**

ii) Layer Normalization (LN)

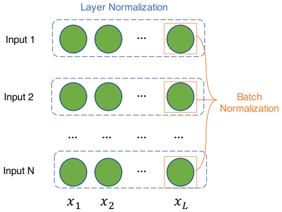


Figure 5: Layer normalization vs. batch normalization for 1-D input (N samples).

LN **immunes to the impact of batch size**, which is suitable to train EVSense model with **dynamic input sequences** and make inference.

Model Enhancement

iii) Customized Output Filtering

After extracting the EV charging events:

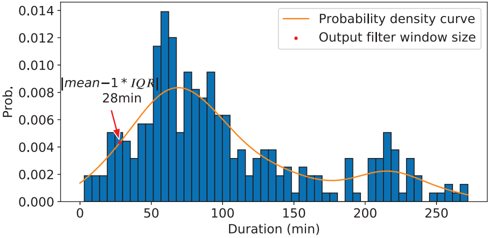


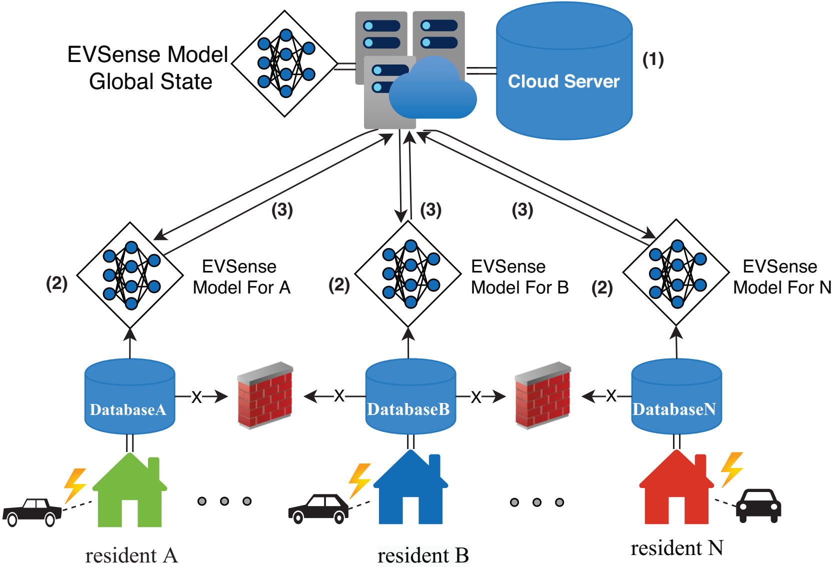
Figure 6: Distribution of EV charging durations.

- **Training-free**, Filter window size $w = |\text{mean} - 1 * IQR|$, Threshold $s = int(0.9 * w)$ in our implement
- Computational complexity is $O(n)$

Algorithm 1: Customized Output Filtering

Input: Resulting charging states $\hat{y}_i, 0 \leq i \leq n$, threshold s, window size w
Output: Filtered charging states
Initialize: an empty Stack S, a counter $c = 0$

```
for i ← 1 to n do
    if S is empty then
        if ŷ_i = 0 then
            continue
        else
            S PUSH i, c+ = 1
        end
    else
        if length of S < w then
            if ŷ_i = 0 then
                S PUSH i
            else
                S PUSH i, c+ = 1
            end
        else
            if c <= s then
                ŷ_j ← 1 for all j POP from S
            else
                ŷ_j ← 0 for all j POP from S
            end
            c ← 0
        end
    end
end
```



(1) Cloud model compression
(2) Local model personalization
(3) Cloud global state update, federated averaging and local model updating

EVSense with Federated Transfer Learning

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1. Global state training:

$$\arg\min_{\theta} f_g(\theta) = \frac{1}{n}\sum_{i=1}^{n} \mathcal{L}\left(x_i, y_i; \theta\right) \tag{5}$$

   Cloud model compression uses the unstructured L1-norm based pruning approach [9]. Freeze all parameters except for the fully connected layers. Send part of labeled data and compressed model.

2. Local model personalization:

$$\arg\min_{\theta} f_c(\theta) = \mathcal{L}_{\text{Supv}} + \lambda \cdot \mathcal{L}_{\text{Unsupv}} \tag{6}$$

$$\mathcal{L}_{\text{User}} = \mathcal{L}_{\text{Supv}} + \lambda \cdot \frac{1}{4d^2}\left\| C_g - C_c \right\|_F^2 \quad (CORAL)\ [3] \tag{7}$$

3. Cloud global state update, federated averaging and local model updating.

$$\theta_{t+1} = \frac{1}{k}\sum_{i=1}^{k} \theta_t^i \tag{8}$$

Dataset

- **Pecan Street:** [12]
  6 residents, 2018-01-01 to 2018-12-31, 1min sampling rate.
  1. Extracted 2044 EV charging events in total: 285(No.661), 447(No.1642), 608(No.4373), 213(No.6139), 400(No.8156), 91(No.3000).
  2. Spring: 2018-01-01 ∼ 2018-03-31 Summer: 2018-05-01 ∼ 2018-07-31. Both period first two months are used for training and third for testing.
- **Synthetic data:**
  31 residents, resample the raw data with 1-min interval. Use the first 2/3 of the selected period for training and the remaining for testing.
  As there are no EVs in these residences, we then added random EV charging events from the Pecan Street dataset.
  1. REDD [8]: Total 6 US houses. Periods of 2011-04-19 ∼ 2011-05-18 for houses 1-5 and 2011-05-22 ∼ 2011-06-13 for house 6.
  2. UK-DALE [7]: Total 5 UK houses of 4∼54 appliances. For house 1, 2016-04-01 ∼ 2016-06-30 is selected, while for the other 4 houses, 2013-05-01 ∼ 2013-07-31 is selected.
  3. REFIT [10]: Total 20 households. Period from 2014-05-01 to 2014-07-31 for all 20 residences.

Experiment Setting

1. **Cloud & Edge Configuration**
   - Cloud server: 4*NVIDIA TITAN V GPUs, 36*Intel Xeon Gold-6150 CPUs.
   - Edge device: Raspberry Pi 4B, 1.5GHz quad-core 64-bit ARM CPU and a 2GB SDRAM.
2. **Benchmarks**
   - Learning-based approach: The factorial hidden Markov model (FHMM) [11, 5, 20].
   - Rule-based approach [18].
3. **Performance Metrics: F1-score**, Accuracy, Precision, Recall.

Experiment Results: Precision and Robustness

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i) Spring Time

EV charging loads are easily distinguished from little high-power loads, such as from an AC. **EVSense** thus has excellent performance, with an ***Avg. F1-score* of** 0.83 while rule-based model is 0.81 and FHMM model is 0.58.

ii) Summer Time and Synthetic Data:

Dataset	*Accuracy* (%)			*Recall* (%)			*Precision* (%)			*F1-score* (%)		
	FHMM	Rule-based	EVSense	FHMM	Rule-based	EVSense	FHMM	Rule-based	EVSense	FHMM	Rule-based	EVSense
Avg. (Pecan St.)	84.04	95.38	**97.87**	38.16	81.11	**93.50**	66.93	52.86	**75.46**	44.68	59.39	**81.94**
Avg. (REDD)	99.52	99.58	**99.93**	89.55	**98.15**	97.58	95.01	77.81	**99.21**	91.19	86.38	**98.38**
Avg. (UK-DALE)	99.01	99.45	**99.83**	72.00	**100**	92.53	98.12	62.68	**99.35**	80.43	74.21	**95.80**
Avg. (REFIT)	85.64	99.43	**99.82**	78.09	**97.84**	92.34	97.19	77.01	**99.12**	85.65	85.69	**95.58**

Table 1: A comparison of EVSense, rule-based, and FHMM methods (Pecan St. summer data and synthetic data) shows that EVSense has the best overall F1-scores.

EVSense model yields higher precision and robustness.

Experiment Results: Precision and Robustness

Figures showing the aggregated load (top), ground-truth EV charging events (middle) and predictions given by EVSense (bottom), respectively.

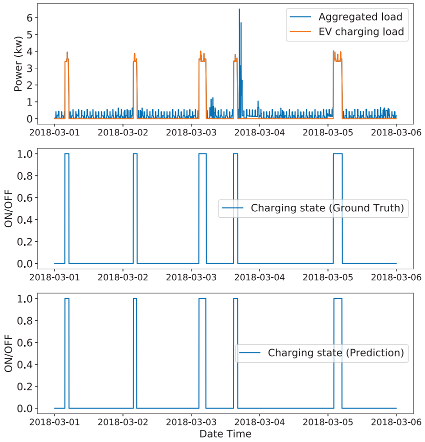

Figure 8: **Note that in spring, EV charging detection is straightforward.**

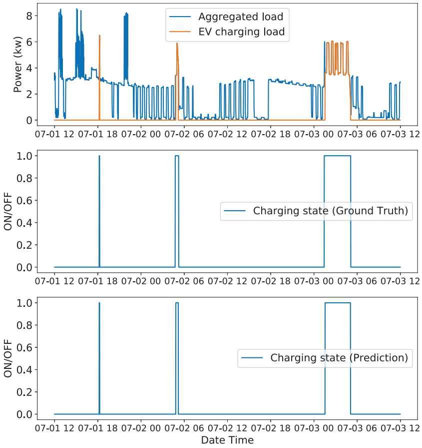

Figure 9: **Note that in summer, detecting charging events is more difficult than in spring.**

Model Compression at Edge Devices

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The trained global model worked on one-month data. **Performance does not degrade with up to about 70% pruning.**

Scalability

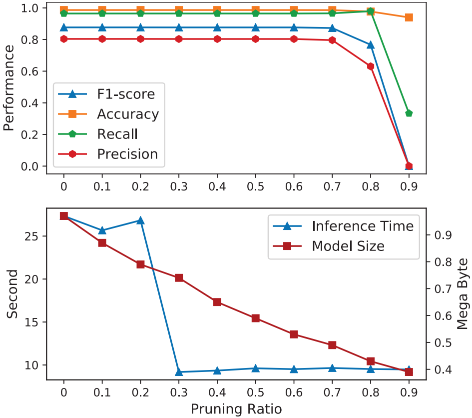

Figure 10: Model performance vs. pruning ratios.

Model Transfer Learning Results

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Unsupervised transfer the trained EVSense model to another residents. We did ***6-way cross validation*** for Pecan Street data. ***Also test EVSense using load profiles without EVs***[2], i.e., those from the original REDD, UK-DALE and REFIT datasets.

Source	*Accuracy* (%)		*Recall* (%)		*Precision* (%)		*F1-score* (%)	
	W/O FTL	FTL	W/O FTL	FTL	W/O FTL	FTL	W/O FTL	FTL
A	95.68	97.75	73.77	95.58	65.14	70.91	62.56	80.16
B	96.21	98.18	79.76	75.39	55.35	93.70	58.05	82.34
C	96.53	98.11	86.55	70.76	51.41	90.17	59.46	80.27
D	94.07	97.95	65.83	71.38	19.54	95.96	29.39	81.11
E	94.14	97.768	79.10	72.51	16.97	96.10	26.32	81.70
F	78.43	97.556	42.04	62.08	88.35	95.03	38.66	74.37
Avg.	92.51	97.89	71.18	74.62	49.46	90.31	45.74	79.99

Avg. Acc (%, Non-EVs on REDD)	99.95 (W/O FTL)	99.99 (FTL)
Avg. Acc (%, Non-EVs on UK-DALE)	99.87 (W/O FTL)	99.98 (FTL)
Avg. Acc (%, Non-EVs on REFIT)	99.83 (W/O FTL)	99.98 (FTL)

Transfer learning greatly improves performance, and the transferred model's performance is close to directly train/test on a target resident data. (*Avg. F1-score*: 79.99% vs.81.94%)

[2] As no positive samples appear in the load profiles without EVs, we only compute the *accuracy* metric to evaluate the correctness of detection.

Changing Sampling Rate & Season, Detection Latency

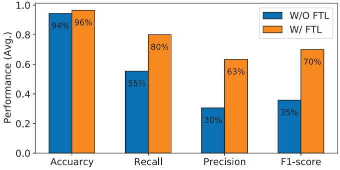

Figure 11: **Sampling rates.** Applying model from 1-min samples to 15-minute samples in summer. Without FTL, performance degrades, but with FTL, there is little degradation in performance compare with directly train/test on 1-min data.

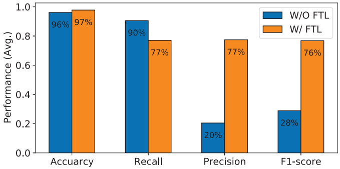

Figure 12: **Seasons.** Applying Summer model in Spring. With FTL, the change in seasons does not appreciably degrade performance.

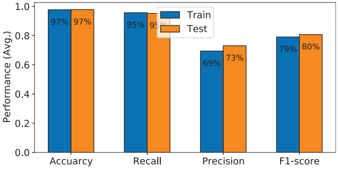

Figure 13: **Input length.** EVSense average performance (train and test) by using 10-minute input sequence lengths instead of 20-minute lengths (Summer samples). Both test and train performance do not appreciably degrade, showing the **low latency**.

Under FTL, EVSense can flexibly and efficiently adapt to different sampling rates, changing length of the input as well as changing data seasons.

Summary

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i) Conclusion

- **EVSense**[3], a DNN-based approach to non-intrusive EV charging detection is proposed and evaluated on both real-world and synthetic datasets which has **higher precision and robustness** for EV charging detection.
- A **federated transfer learning (FTL) framework** is proposed and validated to **address the scalability concern of model deployment** and **user data privacy**. This makes EVSense a feasible solution for large-scale EV monitoring.

Robustness, Low latency, Scalability

ii) Potential Future Work:

1. Enhance the real-time detection capability of the model, from online deep learning (ORL) [1] algorithms aspect.
2. More complex DNN models like transformer [13] can be used for this task, but how to make it fast run on edge devices still have some issues.

[3] Paper code is available on Github: `https://github.com/MathAdventurer/EVSense`

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Thank you for listening!

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