

NeoCharge Smart Electric Vehicle (EV) Charging Algorithms: Assessment of Technical and Economic Benefits

Date: July 2025

Executive Summary

This technical report evaluates the performance of the NeoCharge EV charging optimization algorithm in enhancing residential energy management and its potential contributions to grid support applications. The study, conducted using the advanced research infrastructure at the University of St. Thomas' Center for Microgrid Research (CMR), analyzes real-world load patterns, time-of-use (TOU) rates, and solar generation profiles to assess the algorithm's effectiveness in three key areas: peak demand reduction, cost savings, and solar energy integration.

Key findings demonstrate NeoCharge Algorithm's potential ability to:

- Reduce peak household demand by up to 45% through load shifting
- Lower residential electricity costs up to 26% compared to conventional charging
- Improve system load factor up to 20–25%, benefiting grid stability

The solar-aware version of the NeoCharge algorithm further improves energy efficiency by aligning EV charging with periods of high solar output. Key findings demonstrate NeoCharge Algorithm's potential ability to:

- Up to 98% local solar utilization, reducing midday exports to just 2% of total local solar power generation
- Over 50% of EV energy served directly by residential PV during daytime availability
- Up to 26% reduction in total energy costs under California's NEM 3.0 policy

Optimal results are achieved with a panel current limit of 60 A for peak shaving and load factor improvements, while a reduced current limit of 30–40 A provided greater cost savings at the expense of extended charging durations. For multi-EV scenarios, NeoCharge's algorithm can coordinate multiple EVs with different charging schedules based on their priority order, set in the algorithm. NeoCharge's algorithms could provide dual benefits: mitigating peak loads on distribution infrastructure while enhancing renewable energy integration.

Table of Contents

Executive Summary	ii
1 Introduction	1
1.1 CMR Testbed and Integration	1
2 EV Peak Demand Reduction Simulation	5
2.1 Case 1: Residential House with Small Base Load	5
2.2 Case 2: Residential House with Large Base Load	7
2.3 Case 3: Tesla Long Range Model	9
2.4 Case 4: Impact of Panel Current Limit	11
3 Solar PV and EV Charging Integration	16
3.1 Case 1: Charging During On-Peak Hours	17
3.2 Case 2: Charging During Solar-Generation Hours	19
3.3 Case 3: Impact of Panel Current Limits	21
3.4 Case 4: Impact of Start Time of EV Charging Window	23
3.5 Case 5: Impact of Different EVs	24
3.6 Case 6: Multiple EV Charging Scenario	26
4 Conclusion	29

Chapter 1

Introduction

The primary objective of this technical evaluation is to quantify the impact of NeoCharge’s algorithm on residential peak demand reduction and cost savings, and its ability to integrate EV charging with local solar generation. The study simulates different types of residential homes and EV chargers under various charging scenarios, examining how load profiles and electricity costs change with and without the NeoCharge algorithm. Additionally, the analysis incorporates solar production data to assess how effectively NeoCharge’s solar-aware algorithms can improve local energy self-consumption under California’s Net Energy Metering (NEM) 3.0 policy. By combining time-of-use (TOU) pricing models, dynamic load profiles, and solar generation data, this evaluation provides insights into how intelligent EV charging can enhance residential energy efficiency while supporting broader grid reliability goals.

1.1 CMR Testbed and Integration

To evaluate the performance of NeoCharge’s optimum EV charging algorithm, the Center for Microgrid Research (CMR) team integrated the software algorithm with advanced state-of-the-art real-time testbeds. The testbed models a modern residential energy system equipped with rooftop solar photovoltaic (PV) generation, a Level 2 EV charger, and multiple household appliances such as air conditioner, freezer, water heater, etc, all operating under time-varying load conditions. The EV is modeled with a two-level charger where the charger nominal power, battery capacity, and charging rates can be user-defined. So, the testbed can be used for any EV configurations for NeoCharge’s algorithms. The residential house load is modeled as a variable load which can be simulated using different load profile. All the load power of the house is aggregated to show the panel power in the testbed.

Figure 1.1 illustrates the structure of the residential testbed used in this study. The home draws power from the grid, its rooftop solar system, and power is distributed to loads such as an EV charger and various household appliances. The household load profiles are obtained from Pecan Street¹ and

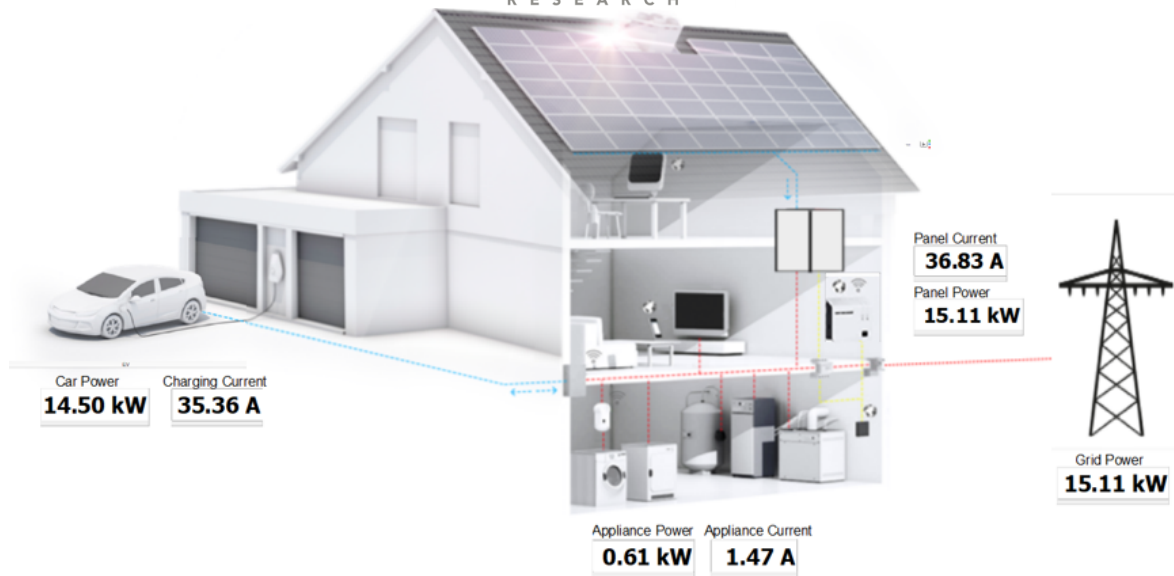


Figure 1.1: CMR residential testbed.

TOU prices are provided by NeoCharge. Pecan Street data set contains residential load profile for different areas in USA. The load profile contains power data with 1 minute resolution that includes different appliance power, as well as rooftop solar pv generation profile (houses that have rooftop solar). CMR Team is able to obtain load profile for 3 areas that include California, New York, and Texas. Figures 1.2 and 1.3 present the real-world load profile of a residential home at a city in Texas and New York, respectively.

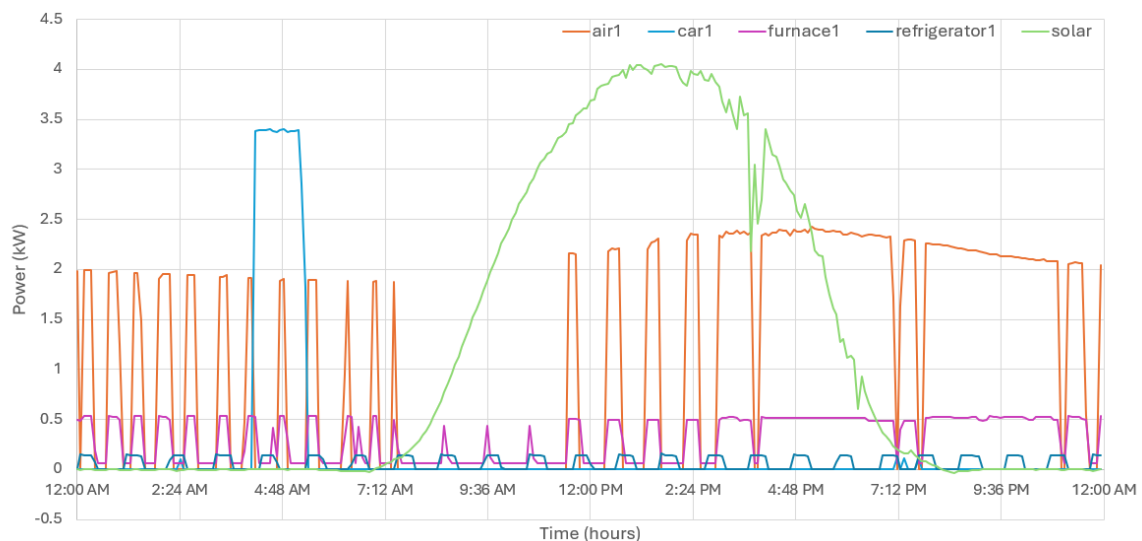


Figure 1.2: A Residential load and solar profile in Texas obtained from Pecan street dataset.

¹Pecan Street Inc., *Dataport*, available at www.pecanstreet.org/dataport, (Accessed: 10 March 2025).

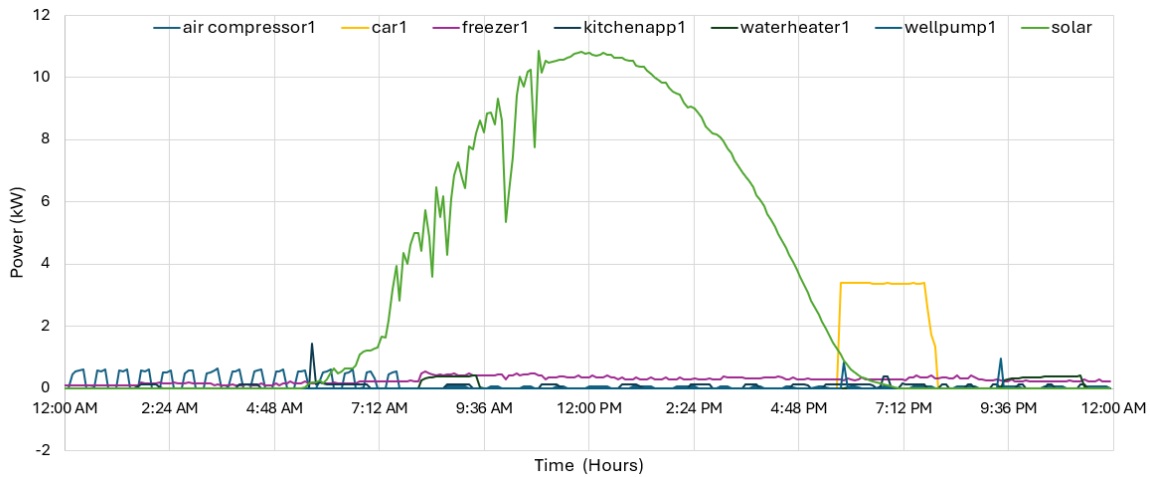


Figure 1.3: A Residential load and solar profile in New York obtained from Pecan street dataset.

To facilitate modular and automated testing approach, the CMR team developed a workflow for integrating NeoCharge’s algorithm with the testbed, shown in Figure 1.4. This process allows the implementation of digital real-time simulation of CMR Microgrid testbed with NeoCharge algorithm.

The workflow begins with an input measurement CSV containing 5-minute interval data on household load, EV charging demand, solar generation, and utility rate structures depending on which algorithm is being tested. These input parameters come from the CMR residential testbed. As the algorithm take current data as an input, the power data is converted to current data before sending them to NeoCharge’s algorithms. These input measurements are then processed by NeoCharge’s algorithm, which generates an optimized charging schedule for EV charging. The output signals from the algorithm are saved and sent into the CMR residential testbed. The optimum charging rates sent by the algorithm are taken as input signals for the EVs in CMR testbed. These

The remainder of the report is organized as follows. Chapter 2 presents simulation-based analyses

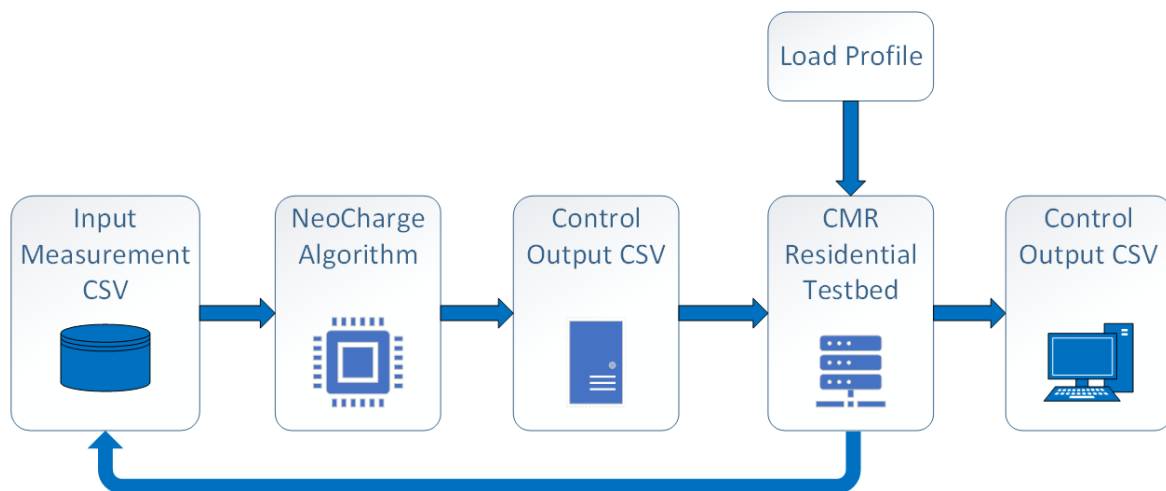


Figure 1.4: Flowchart of NeoCharge algorithm integration with the CMR testbed.

evaluating the effectiveness of NeoCharge's simple EV algorithm in reducing EV-driven peak demand under various residential scenarios, including homes with differing base loads, different EV models, and varying panel current limits. Chapter 3 explores the effectiveness of NeoCharge's solar-aware EV algorithm. This section addresses charging during on-peak and solar-generation hours, the influence of panel current limitations, variations in charging start times, and the performance of different EV models, including multi-EV charging scenario. Finally, Chapter 4 summarizes key findings and provides concluding remarks.

The NeoCharge's algorithms that CMR Team evaluated for this report are:

- Simple Single EV Algorithm version 3 (received May 14, 2025)
- Solar-aware Algorithm version 3 (received May 14, 2025)

Chapter 2

EV Peak Demand Reduction Simulation

In order to test the NeoCharge algorithm with simple EV algorithm, various test cases are simulated. The simulations performed at CMR aim to evaluate the algorithm's ability to reduce residential peak demand, shift EV charging away from high-cost periods, and improve overall load factor. Each case explores different charging windows, time constraints, and load conditions to assess the flexibility and robustness of the NeoCharge's algorithms.

2.1 Case 1: Residential House with Small Base Load

This case investigates the impact of NeoCharge's algorithm on reducing residential peak demand and energy costs across different EV charging strategies. Key specifications for this study:

- The maximum current capacity for this house is set at 48 A
- Tesla model 3 battery size is 57.5 kWh and the daily consumed energy of the house is around 31.7 kWh without EV
- The EV is charged from 10% to 90 %
- Two charging windows are simulated, on-peak (4 PM–10 PM) and off-peak (12 AM–3 PM), under both flat and TOU utility rate structures

Four distinct scenarios are analyzed: Off-Peak Charging without NeoCharge, Off-Peak Charging with NeoCharge, On-Peak Charging without NeoCharge, and On-Peak Charging with NeoCharge. Figures 2.1 and 2.2 present the total household power consumption profiles across a 24-hour period for off-peak and on-peak charging scenarios with and without NeoCharge algorithm, respectively.

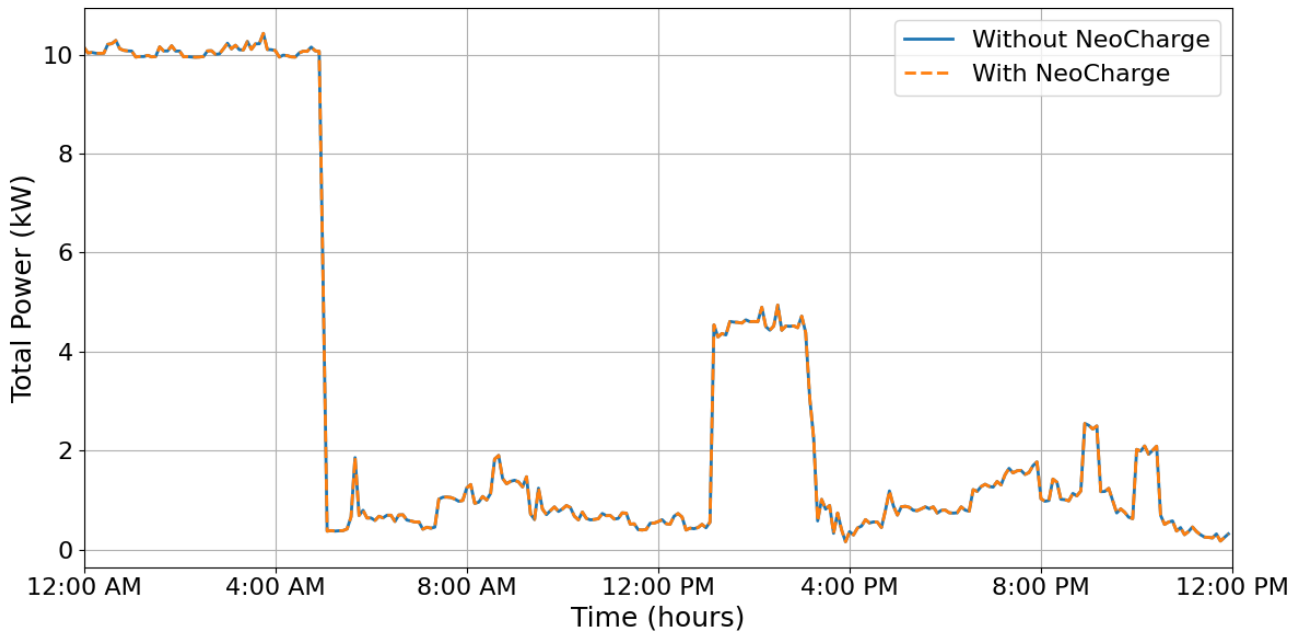


Figure 2.1: Total power consumption during off-peak charging for small residential base load.

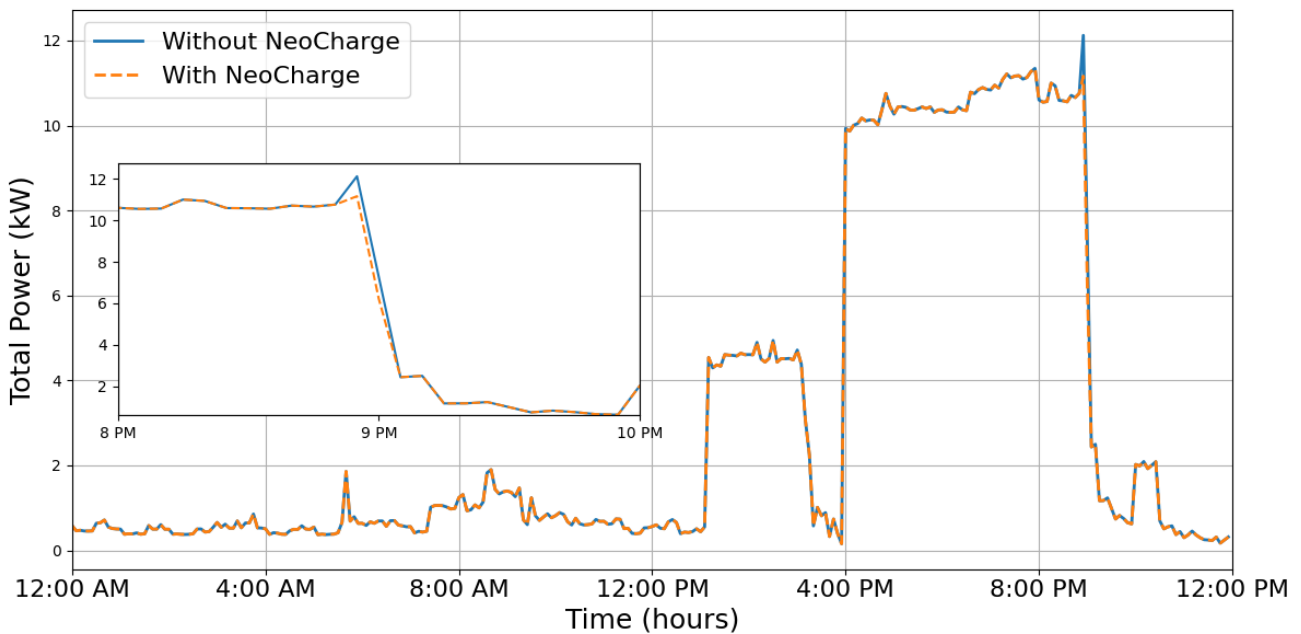


Figure 2.2: Total power consumption during on-peak charging for small residential base load.

In the off-peak scenario, shown in 2.1, both charging strategies result in nearly identical load curves. Since charging occurs during low-demand hours, NeoCharge has minimal room for optimization. Consequently, the energy cost and peak demand remain unchanged with or without the algorithm. In contrast, the on-peak scenario, shown in 2.2, highlights NeoCharge’s ability to reshape the load curve by distributing the EV charging load more efficiently. While the total energy consumption remains constant as the EV needs to be charged fully, NeoCharge’s algorithm reduced the peak load from 12.12 kW to 11.35 kW and shifted the peak occurrence one hour earlier (from 8:55 pm to 7:55

Table 2.1: Summary of Key Metrics for small residential base load

Key Parameter	Off Peak without NeoCharge	Off Peak with NeoCharge	On Peak without NeoCharge	On Peak with NeoCharge
Flat rate Cost (\$)	14.24	14.24	14.24	14.24
Tou Cost (\$)	16.88	16.88	28.54	28.53
Peak Load (kW)	10.43	10.43	12.12	11.35
Peak Load time	3:45 am	3:45 am	8:55 pm	7:55 pm
Average Load (kW)	3.12	3.12	3.12	3.12
Load Factor (%)	29.93	29.93	25.76	27.46
EV Charging Time (hour)	5.083	5.083	5.083	5.083
EV Energy Consumed	48.28	48.28	48.28	48.28
Total Energy Consumed (kWh)	74.94	74.94	74.94	74.94

pm). This indicates an improvement in load balancing during high-demand periods. A detailed summary of key metrics is shown in Table 2.1. There is no difference in cost for flat rate as total energy consumption remains the same. However, under TOU pricing, NeoCharge provided a small but measurable peak reduction of 0.77 kW during on-peak charging, translating to a 6.35% decrease in peak load. The load factor improved from 25.76% to 27.46% with NeoCharge in the on-peak case. The TOU cost savings are marginal between with and without NeoCharge, dropping from \$28.54 to \$28.53, reflecting minor peak time reshaping.

2.2 Case 2: Residential House with Large Base Load

This case represents a household with a significantly higher baseline power consumption than in Case 1. The daily consumed energy for this house is around 96 kWh without EV. The rest of the parameters are similar as case 1. The goal is to evaluate the performance of NeoCharge’s optimization under increased total energy demand, particularly its ability to reduce peak demand and energy cost. Figures 2.3 and 2.4 show the total power demand profile across the 24-hour period under off-peak and on-peak charging strategies, respectively.

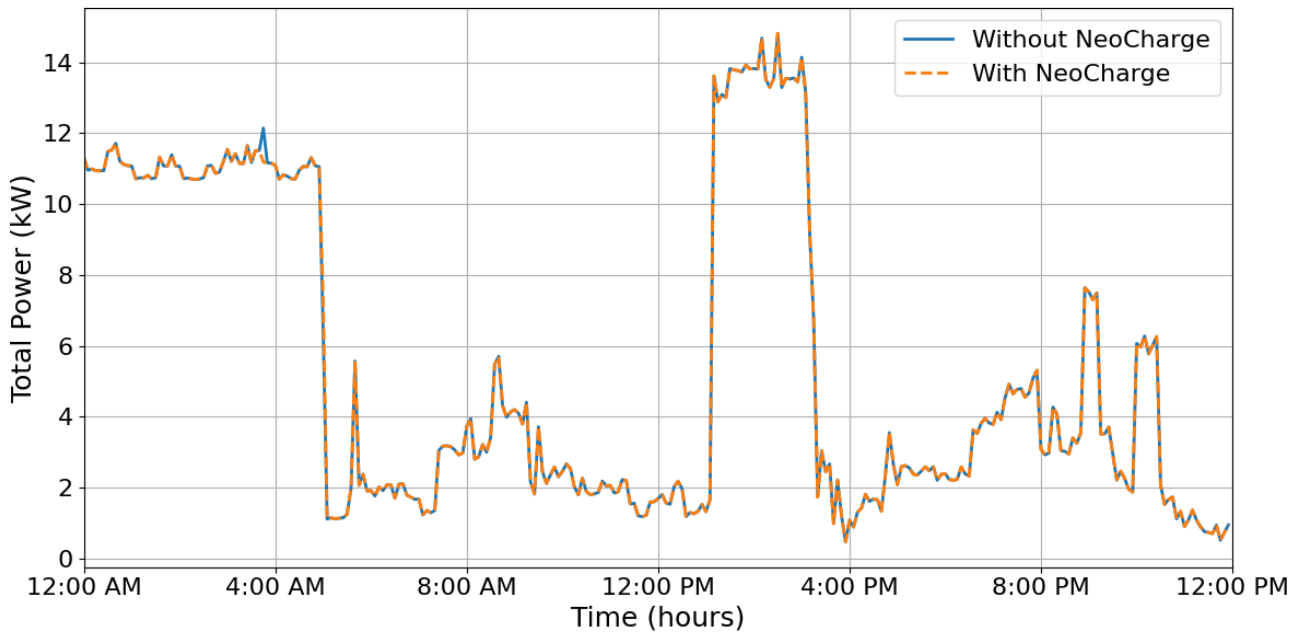


Figure 2.3: Total power consumption during off-peak charging for large residential base load.

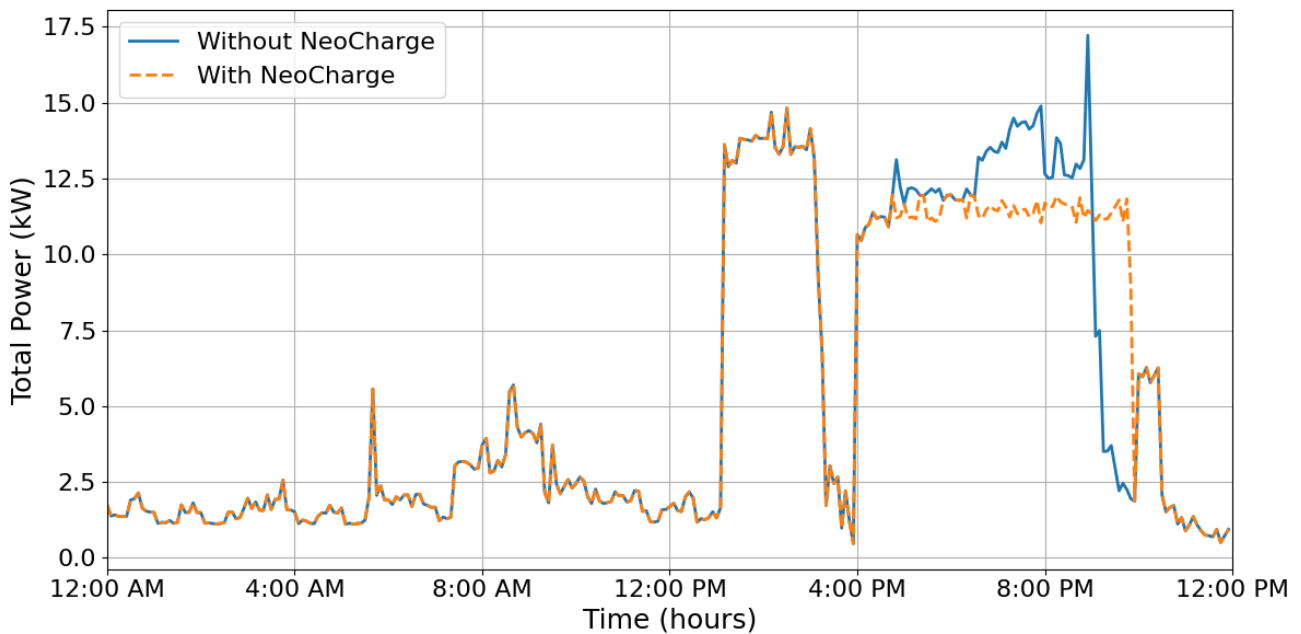


Figure 2.4: Total power consumption during on-peak charging for large residential base load.

In the off-peak scenario, NeoCharge had no effect on peak reduction since charging already occurs in low-load periods. In the on-peak case, NeoCharge successfully flattened the power curve between 5 PM and 9 PM, significantly lowering the peak demand from 17.22 kW to 14.82 kW, a 13.9% reduction. The algorithm shifted the peak load occurrence from 8:55 PM to 2:30 PM for on-peak charging scenario, overlapping with baseline non-EV demand but outside the typical evening peak.

A summary of the key performance metrics is presented in Table 2.2. TOU cost dropped slightly from \$43.95 to \$43.32 with NeoCharge during on-peak charging, a 1.04% decrease in cost. Peak de-

Table 2.2: Summary of Key Metrics for large residential base load

Key Parameter	Off Peak without NeoCharge	Off Peak with NeoCharge	On Peak without NeoCharge	On Peak with NeoCharge
Flat rate Cost (\$)	24.37	24.37	24.37	24.37
Tou Cost (\$)	32.30	32.30	43.95	43.32
Peak Load (kW)	14.82	14.82	17.22	14.82
Peak Load time	2:30 pm	2:30 pm	8:55 pm	2:30 pm
Average Load (kW)	5.34	5.34	5.34	5.34
Load Factor (%)	36.06	36.06	31.04	36.06
EV Charging Time (hour)	5.083	5.083	5.083	5.916
EV Energy Consumed (kWh)	48.28	48.28	48.28	48.28
Total Energy Consumed (kWh)	128.26	128.26	128.26	128.26

mand is reduced by 2.4 kW, which has important implications for transformer and feeder loading. Load factor improved from 31.04% to 36.06%, indicating better power consumption curve. EV charging time slightly increased with NeoCharge in the on-peak scenario from 5.083 hours to 5.916 hours, reflecting throttled but extended charging to reduce peak overlap.

2.3 Case 3: Tesla Long Range Model

Since there are minimal improvements in off-peak periods, we concentrate on on-peak charging scenarios. In this case study, a larger EV is considered with a different residential load profile. Key specifications for this study:

- EV is assumed to be a Tesla Long range model
- The battery capacity of the EV is 82 kWh with different house loads where daily energy consumption of the house without EV is around 148 kWh.
- The maximum current capacity for this house is set at 80 A.

The household exhibits both high energy usage and peak coincidence between EV charging and overall household load. This case is representative of worst-case grid stress conditions due to uncoordinated charging behavior. Figure 2.5 shows a pronounced difference between the baseline and optimized scenarios. Without NeoCharge, the household experiences sharp spikes between 20 and 22 hours, reaching a peak of 25.76 kW. With NeoCharge, these spikes are significantly flattened, capping peak load at 19.32 kW. The optimization also shifted the peak from 20:35 to 19:45, redistributing EV charging

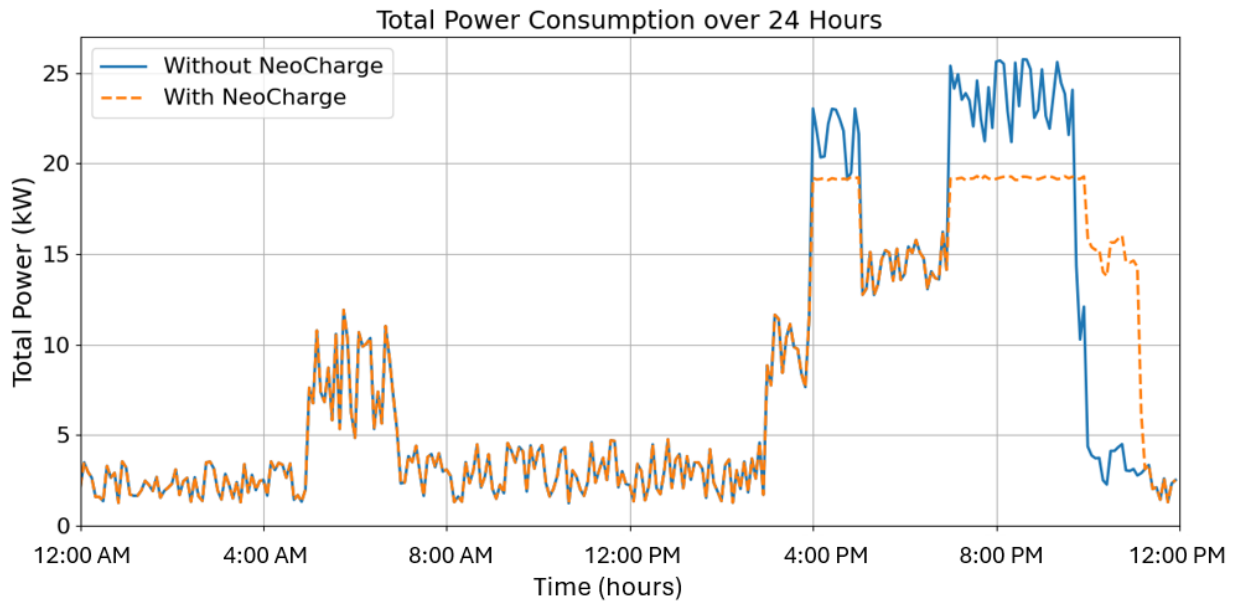


Figure 2.5: Total power consumption during on-peak charging for Tesla long range model.

load into less congested time blocks. So, the NeoCharge’s algorithm is able to intelligently throttle the charging power to reduce stress without compromising total energy delivery.

Key performance metrics for Case 3 are summarized in Table 2.3. From the table, it can be observed that Peak demand is reduced by 6.44 kW, a 25% reduction and the load factor improved significantly from 30.17% to 40.23%, indicating a more uniform load profile. NeoCharge extended the EV charging time from 5.75 to 7.25 hours, distributing the charging load more evenly. TOU cost dropped slightly from \$66.80 to \$65.67, a 1.69% reduction in overall cost.

Table 2.3: Summary of Key Metrics for Tesla long range model

Key Parameter	On Peak without NeoCharge	On Peak with NeoCharge
Flat rate Cost (\$)	35.44	35.44
Tou Cost (\$)	66.80	65.67
Peak Load (kW)	25.76	19.32
Peak Load time	20:35	19:45
Average Load (kW)	7.77	7.77
Load Factor (%)	30.17	40.23
EV Charging Time (hour)	5.75	7.25
EV Energy Consumed (kWh)	66.24	66.24
Total Energy Consumed (kWh)	186.52	186.52

2.4 Case 4: Impact of Panel Current Limit

This case focuses on the impact of panel load current limit on savings, peak load, load factor of the residential home, and charging time of EV. Panel load current limit can be adjusted by the user in the algorithm. The first part of this case study explores its impact on off-peak charging and the later part focuses on on-peak charging scenarios.

Figure 2.6 illustrates the total household power consumption profiles over a 24-hour period for NeoCharge algorithm operating under different current limits when EV is charged during off-peak hours. With lower current limits, load is shifted throughout the day making it longer to charge. However, with higher current limits, EV can be charged faster while increasing the peak load current during the off-peak hours.

Detailed summary of the off-peak study is provided in Table 2.4. With the strictest current limit of 30 A, NeoCharge reduced the peak load by 38.75% to 14.35 kW and achieved the highest load factor (54.96%). However, this came at the cost of a higher TOU energy cost of \$55.35 exceeding base cost, due to extended charging across less favorable pricing intervals. The EV charging time in this scenario increased to 22.33 hours, making it impractical. As the current limit is gradually relaxed, peak reduction decreases and the EV charging window becomes more compact, resulting in similar cost to base cost. In order to avoid any additional cost, panel current limit for this specific residential building needs to be set at a minimum of 50 A.

The impact on savings with NeoCharge algorithm during off-peak hours is none due to low base

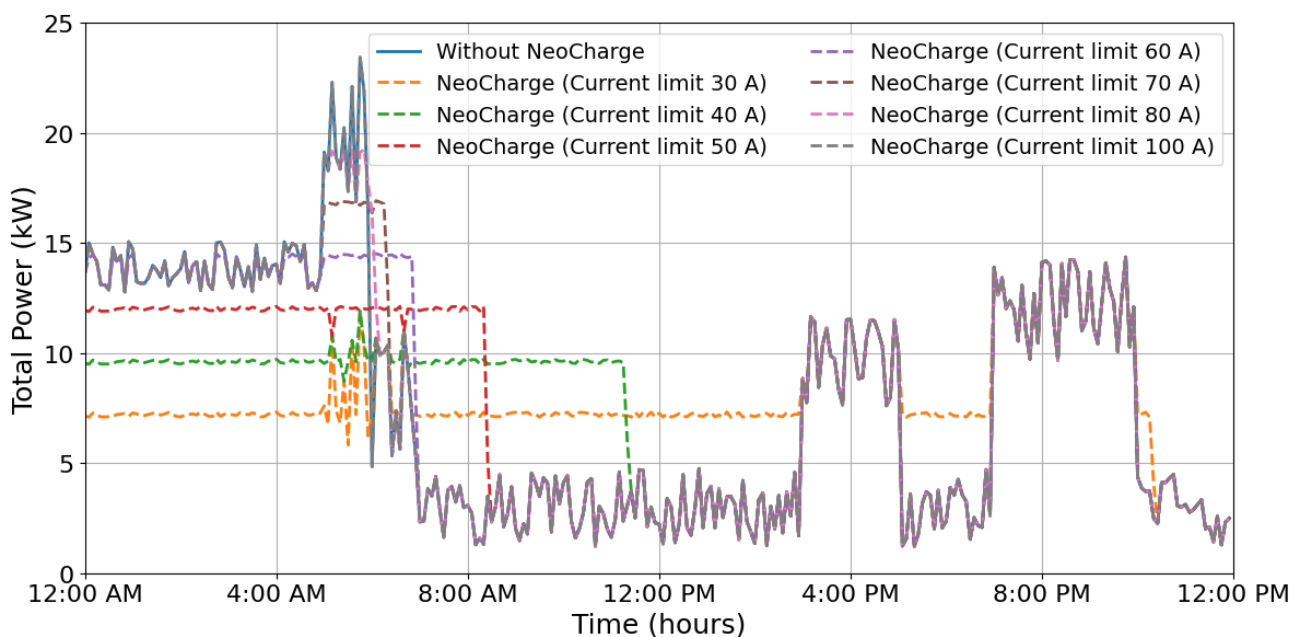


Figure 2.6: Total power consumption during off-peak charging with varying panel current limit.

Table 2.4: Summary of NeoCharge algorithm’s performance under different current limits during off-peak hours

Key Parameter	without NeoCharge	NeoCharge (limit= 30 A)	NeoCharge (limit= 40 A)	NeoCharge (limit= 50 A)	NeoCharge (limit= 60 A)	NeoCharge (limit= 70 A)	NeoCharge (limit= 80 A)	NeoCharge (limit= 100 A)
Tou Cost (\$)	51.92	55.35	52.71	51.92	51.92	51.92	51.92	51.92
Savings (\$)	0	-3.43	-0.79	0	0	0	0	0
Peak Load (kW)	23.43	14.35	14.35	14.35	14.52	16.91	19.27	23.43
Peak Load Reduction (%)	0	38.75	38.75	38.75	38	28	17.75	0
Peak Load Start Time	5:45	21:45	21:45	21:45	2:45	6:05	5:25	5:45
Load Factor (%)	33.67	54.96	54.96	54.96	54.34	46.65	40.94	33.67
EV charging hour	6.0	22.33	11.33	8.42	6.92	6.33	6.08	6.0

power load and low TOU rate. However, NeoCharge algorithm has an impact on charging time and peak reduction during that time. Figure 2.7 highlights the relationship between current limit and peak load reduction, as well as EV charging time. At lower current limits (30–60 A), NeoCharge achieves maximum peak reduction up to 38.75% but at the cost of prolonged charging hours, with a maximum charging time of 22.33 hours. As the current limit increases, it improves charging times but decreases peak reduction. The best case for these scenarios is to set the panel current limit to 60 A, shown with the dotted vertical line where the distance between the two plots is the highest.

Next, the same study is conducted during on-peak times where the analysis shows that NeoCharge

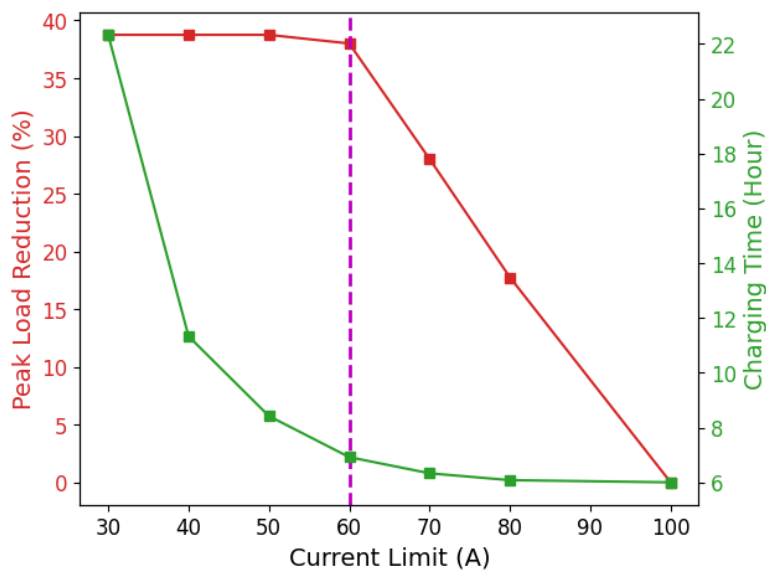


Figure 2.7: Trade-off between peak load reduction and EV charging duration under varying current limits.



algorithm can reduce both the peak load and electricity cost. Figure 2.8 illustrates the total household power consumption profiles over a 24-hour period for NeoCharge algorithm operating under different current limits when EV is charged during on-peak hours. During on-peak periods, the baseline scenario exhibits a demand spike peaking at 25.87 kW at 9:45 PM. In contrast, the NeoCharge algorithm shifts and distributes the charging load to flatten the peak, based on the setpoint of current limit.

Performance metrics of NeoCharge algorithm during on-peak scenarios are summarized in Table 2.5. With lower current setpoint, NeoCharge achieved the highest peak reduction of 44.5%, lowering peak demand to 14.35 kW. This also yielded the best load factor improvement, from 30.48% to 54.96%. However, the lower current limits came at the cost of longer charging times, with EV charging hours extending up to 14.33 hours for the 40 A setting. Despite longer charging durations, the 40 A case resulted in the highest energy cost savings, reducing the TOU cost from \$67.79 to \$56.04, a 17% improvement. As the current limit increases peak reduction, and savings decline steadily but charging time improves.

To further highlight the trade-offs between performance and flexibility under varying current limits, Fig. 2.9 visualizes how cost savings correlate with peak load reduction and EV charging time, respectively. Fig. 2.9a shows that both peak load reduction and energy savings decrease consistently as the current limit increases. At 40 A, NeoCharge achieves the highest savings, with over 44% peak load reduction and up to 17% cost savings. However, Fig. 2.9b shows the charging time required to achieve these benefits is 14.33 hours which may not be feasible if EV needs to be operated early in the morning. So, optimal current limit setpoint will be based on user preference. For example, if charging

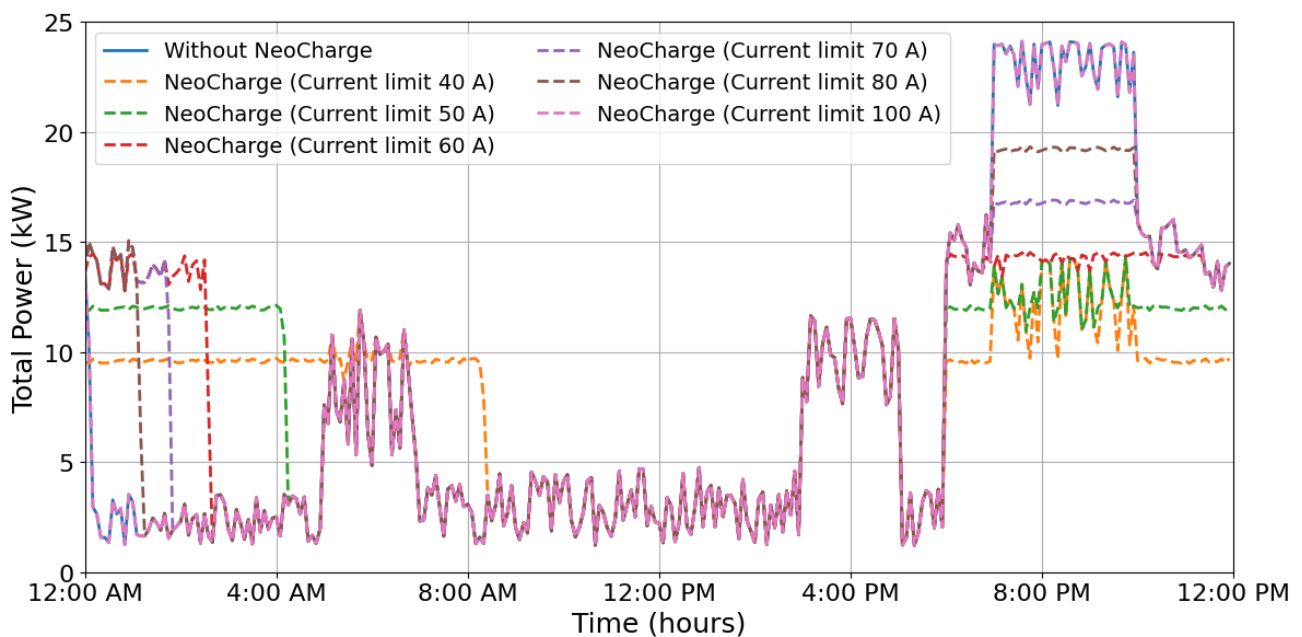


Figure 2.8: Total power consumption during on-peak charging with varying panel current limit.

needs to be completed within 12 hours, the optimum panel current set point will be 60 A. This will reduce costs around 11% instead of maximum savings of 17% and peak load reduction will be around 44%.

The results of the all case studies show that the NeoCharge optimization algorithm can significantly reduce household peak load, improve the overall load factor, and reduce cost across a range of residential charging scenarios. In both off-peak and on-peak studies, NeoCharge demonstrates the ability to flatten demand curves, with peak load reductions of up to 45% and load factor improvements ex-

Table 2.5: Summary of NeoCharge algorithm’s performance under different current limits during on-peak hours

Key Parameter	without NeoCharge	NeoCharge (limit= 40 A)	NeoCharge (limit= 50 A)	NeoCharge (limit= 60 A)	NeoCharge (limit= 70 A)	NeoCharge (limit= 80 A)	NeoCharge (limit= 100 A)
Tou Cost (\$)	67.79	56.04	57.58	60.31	62.52	64.32	67.40
Savings (\$)	0	11.75	10.21	7.58	5.27	3.47	0.39
Savings (%)	0	17	15	11	8	5	0.5
Peak Load (kW)	25.87	14.35	14.35	14.52	16.92	19.32	24.11
Peak Load Reduction (%)	0	44.5	44.5	44	35	25.3	6.8
Peak Load Start Time	21:45	21:45	21:45	19:45	19:45	19:45	19:35
Load Factor (%)	30.48	54.96	54.96	54.34	46.62	40.83	32.72
EV charging hour	6.0	14.33	10.17	8.58	7.75	7.17	6.083

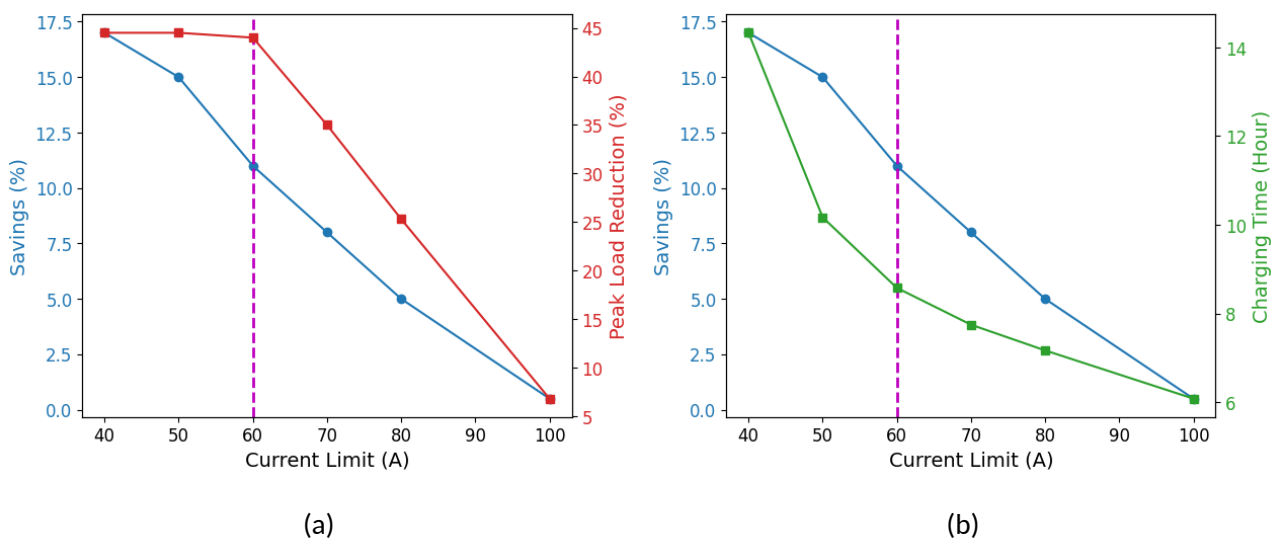


Figure 2.9: Relationship between TOU cost savings under varying current limits with (a) peak load reduction and (b) EV charging time

ceeding 20 percentage points in some configurations. Even though NeoCharge is not able to reduce costs for off-peak charging, it can reduce costs up to 17% for on-peak charging scenarios under TOU pricing. From the analysis of the results, it is recommended that panel current limit should be set at 60 A for off-peak and on-peak charging scenarios for optimum result. However, the panel current limit can be lowered to achieve more savings in cost of EV charging durations for on-peak charging scenarios.

Chapter 3

Solar PV and EV Charging Integration

To evaluate NeoCharge’s ability to optimize EV charging in conjunction with residential solar PV generation, a comparative simulation is conducted using a typical summer solar production profile under California’s Net Energy Metering (NEM) 3.0 rate structure. This study aims to assess how NeoCharge’s solar-aware algorithm affects solar utilization, export levels, and grid interaction, while reducing household peak load. Two different scenarios are simulated for this study: one is Without Solar-Aware Optimization where EV charging schedules remain fixed and excess solar is exported to the grid. The other is With NeoCharge with Solar-aware optimization algorithm where EV charging schedules are dynamically adjusted to match solar availability, reducing grid export and increasing solar self-consumption. Weekly compensation under NEM 3.0 for PG&E obtained from Tesla website is shown in Fig. 3.1².

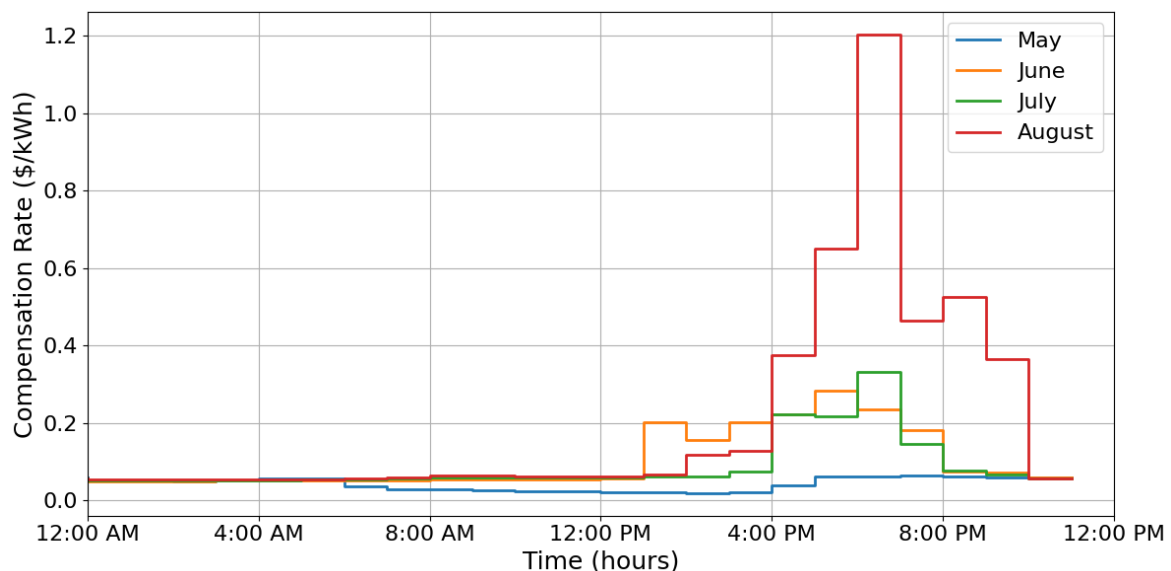


Figure 3.1: Weekly compensation rates under PG&E’s NEM 3.0 during summer 2024.

²Tesla, *Net Billing Tariff (NEM 3.0)*, Available at www.tesla.com/support/energy/solar-panels/learn/net-billing, (Accessed: 10 May 2025).



3.1 Case 1: Charging During On-Peak Hours

The household load and solar generation for a typical summer day for that specific house are obtained from the pecan street data set. For this case, key specifications are:

- EV is assumed to be a Tesla Long range model
- EV started charging on peak time (4 pm)
- The maximum current capacity for this house is set at 80 A.

Figures 3.2 and 3.3 present the full household power distribution, solar availability, and net grid power draw with and without NeoCharge with solar aware algorithm. NeoCharge algorithm enables peak load reduction from 25.76 kW to 19.32 kW which improved load factor from 24.8% to 32.65%. The peak is shifted from 8:35 pm to 7:45 pm. This peak is determined by the maximum allowable current through the house panel, set by NeoCharge’s algorithm.

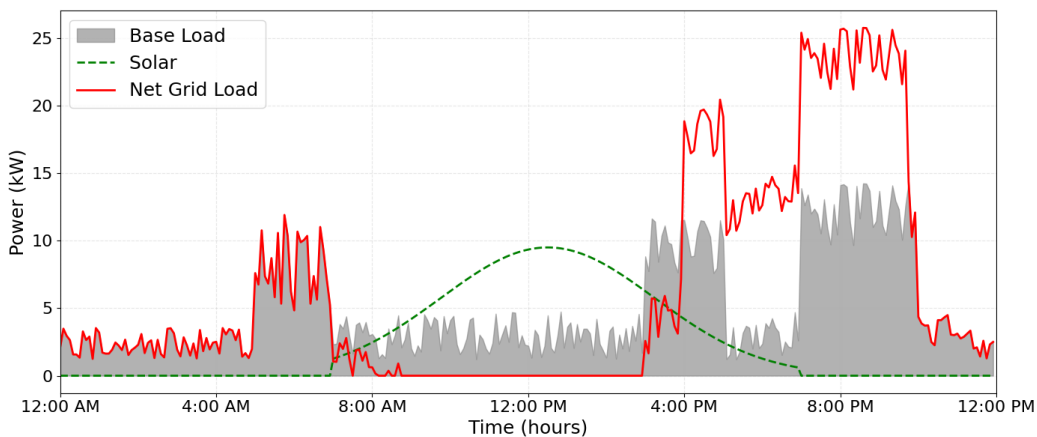


Figure 3.2: Net load and solar generation without NeoCharge optimization.

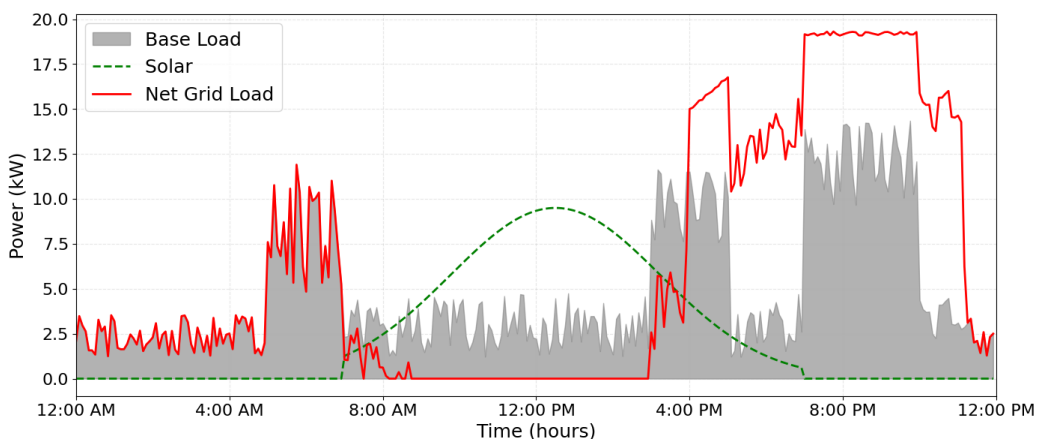


Figure 3.3: Net load and solar generation with NeoCharge’s solar-aware charging algorithm for case 1.

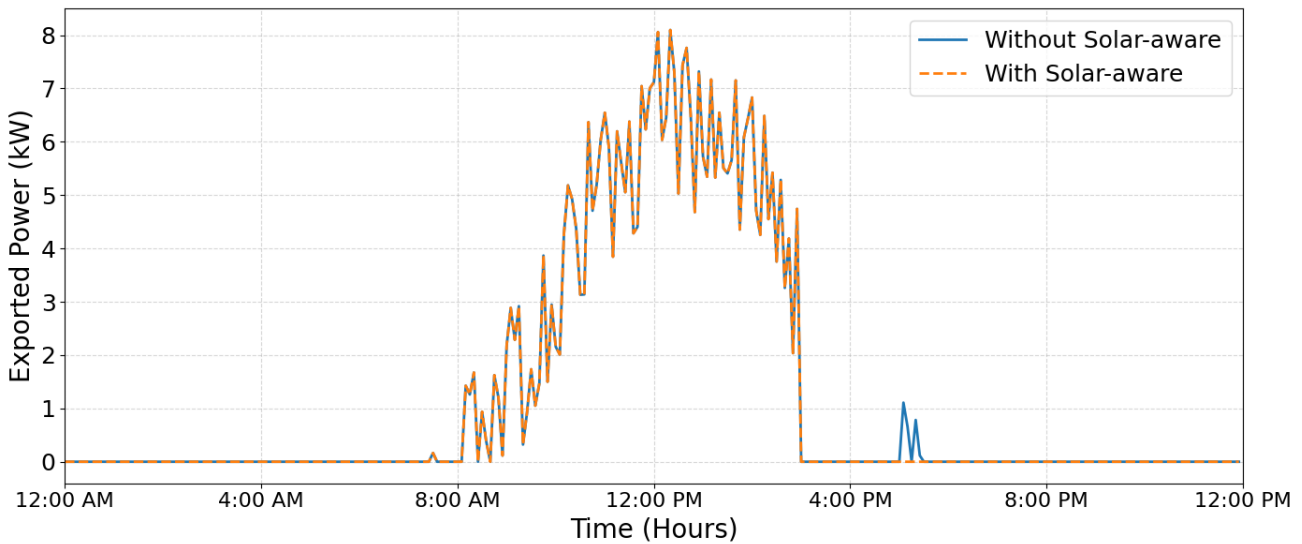


Figure 3.4: Solar power exported to the grid, with and without NeoCharge optimization.

Figure 3.4 shows the comparison between the exported solar power over with and without using solar power for EV charging where red line represents solar-export to grid with solar-aware EV charging and green dashed line represents solar-export to grid without solar-aware EV charging. As expected, charging without optimization results in solar being fully exported, whereas solar-aware charging enables small local consumption, from 5 pm to 6 pm. The difference in solar utilization with and without the algorithm is very small as EV is hardly available during the day for this scenario.

The performance metrics are summarized in Table 3.1. While total solar production remains unchanged at 63.21 kWh, NeoCharge with solar aware algorithm slightly increases solar self-consumption from 32.92 kWh to 33.14 kWh, a 0.67% increase and enables 0.22 kWh of EV energy to be sourced directly from solar, 0.34% of EV load. As a result, solar exported to the grid is reduced by 0.73%. These numbers are small as EV charging time is set from 4 pm.

Table 3.1: Solar-aware charging results for on-peak charging using NeoCharge

Key Parameter	Without NeoCharge+solar	With NeoCharge+solar
TOU Cost (\$) with NEM 3.0 for May	55.8	55.73
TOU Cost (\$) with NEM 3.0 for August	54.53	54.53
Peak Load (kW)	25.76	19.32
Peak Load Time	8:35 pm	7:45 pm
Average Load (kW)	6.39	6.39
Load Factor (%)	24.8	32.65
Solar Produced (kWh)	63.21	63.21
Solar utilization (kWh)	32.92	33.14
Solar export to grid (kWh)	30.29	30.07
EV load served by solar (kWh)	0	0.22



3.2 Case 2: Charging During Solar-Generation Hours

This case explores the impact of solar-aware algorithm when EV is available during the day time of a typical summer. Key specifications for this case:

- EV is assumed to be a Tesla Long range model
- Charging window for the EV is 8 AM – 6 PM
- The maximum current capacity for this house is set at 80 A
- EV has 80% capacity left for charging, i.e. its SOC is 20%.

Figure 3.5 illustrates the total household load distribution, solar generation, and net grid load. Despite daytime charging limits, NeoCharge is able to leverage solar effectively as it is utilizing the solar to charge the EV. As a result, less amount of power will be coming from the grid than previously, reducing the peak load on the house utility meter.

Figure 3.6 shows solar-export comparisons with and without utilizing solar power for EV charging. The significant drop in midday solar exports under NeoCharge algorithm confirms improved local consumption due to EV's availability for charging. From the figure, it can be observed that full solar power is used for charging EV till about 2:00 pm. After that, the solar-export is the same as EV is fully charged as NeoCharge can control the charge rate of the EV.

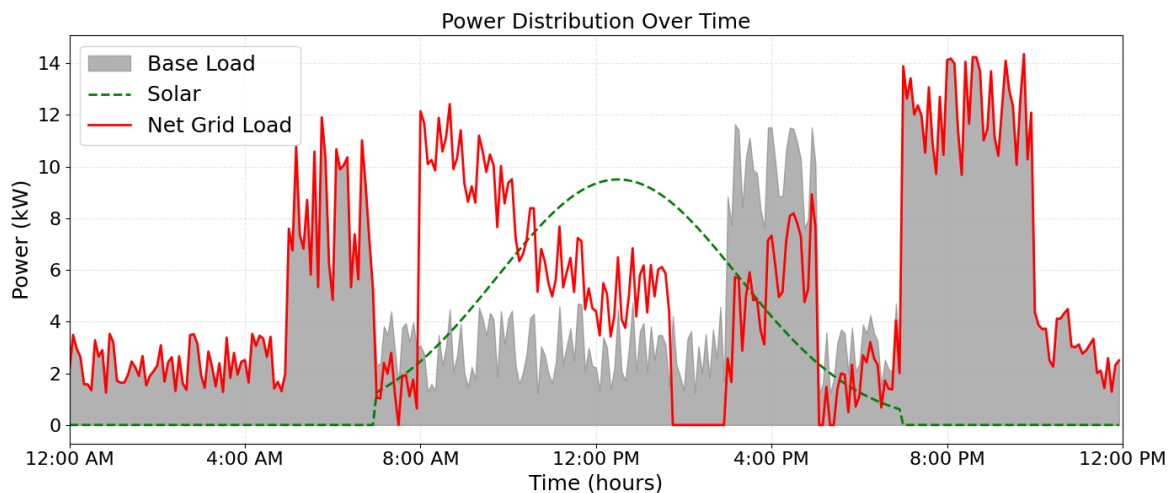


Figure 3.5: Net load and solar generation with NeoCharge's solar-aware charging algorithm for case 2.

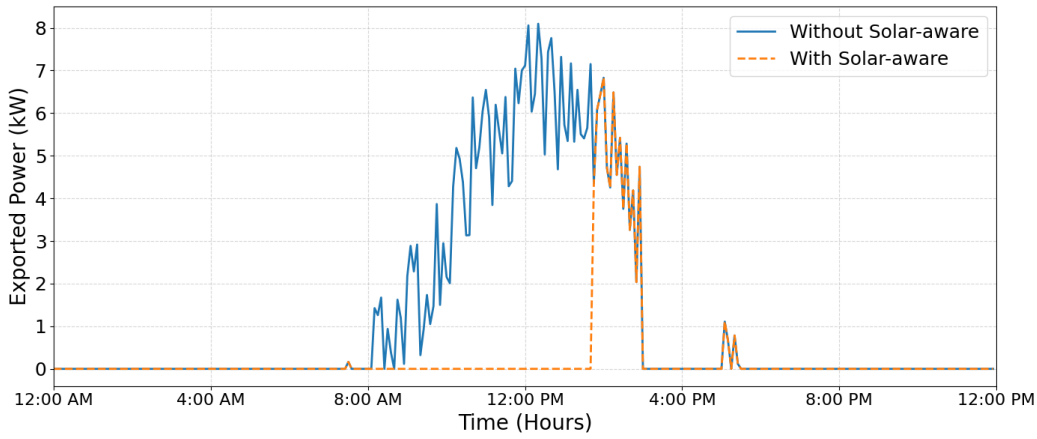


Figure 3.6: Solar power exported to the grid, with and without NeoCharge’s solar-aware algorithm.

Table 3.2: Solar-aware charging results for charging time from 8 AM–6 PM using NeoCharge.

Key Parameter	NeoCharge with solar (8 am - 6 pm)
TOU Cost (\$) with NEM 3.0 for May	39.12
TOU Cost (\$) with NEM 3.0 for August	38.78
Peak Load (kW)	14.35
Peak load time	9:45 pm
Average Load (kW)	5.39
Load Factor (%)	37.56
Solar Produced (kWh)	63.21
Solar utilization (kWh)	56.94
Solar export to grid (kWh)	6.26
EV load served by solar (kWh)	24.02

Table 3.2 summarizes the results, highlighting a dramatic increase in solar utilization. EV load served by solar jumped from 0.22 kWh (previous case) to 24.02 kWh, 36.27% of the EV load is now served by solar. Solar utilization rose to 56.94 kWh from 32.92 kWh, a 42.18% increase. Moreover, solar-export to grid is reduced to 6.26 kWh, a 79.30% decrease in solar export. TOU cost for this case is \$39.12 for May and \$38.78 for August, resulting in cost reduction of 29.80% and 28.88%, respectively. Peak load reduced to 14.35 kW and hence, load factor improved to 37.56%.

This case demonstrates the impacts of aligning EV charging within solar period with NeoCharge’s algorithm. NeoCharge successfully maximized solar self-consumption, improved load factor and reduced cost.

3.3 Case 3: Impact of Panel Current Limits

In this case, the objective is to study the impact of panel current limits on key performance metrics such as solar utilization, solar export to the grid, and load factor, assuming EV is available from 8 am, meaning during the day time. Fig. 3.7 illustrates the solar-export profiles over a 24-hour period for various panel current limits. The baseline scenario exports a substantial amount of mid-day solar to the grid as solar is not utilized by EV. In contrast, NeoCharge’s solar-aware algorithm adjusts EV charging to align with available solar reducing solar-export to the grid. Lower current limits result in longer utilization of available solar, while higher current limits provide shorter charging periods.

Table 3.3 provides percentage savings for different panel current limits utilizing export rate of 4 different months which is also shown in Fig. 3.8. With NeoCharge’s solar-aware algorithm up to 25% savings can be achieved for a house with peak solar power of 10 kW for the month of August. Moreover, minimum savings during summer is around 18% for this case considering Tesla 3 long range EV model with capacity of 82 kWh.

Table 3.3: Savings comparison for NeoCharge Solar-aware algorithm during summer

PG&E Export rate (Month)	Savings with NeoCharge Solar-aware algorithm (%)				
	Current Limit 30 A	Current Limit 40 A	Current Limit 50 A	Current Limit 60 A	Current Limit 80 A
May	21.4	21.0	20.6	20.6	20.6
June	20.5	19.2	19.1	19.1	19.1
July	22.4	18.5	18.1	18.1	18.1
August	25.6	18.2	17.9	17.9	17.9

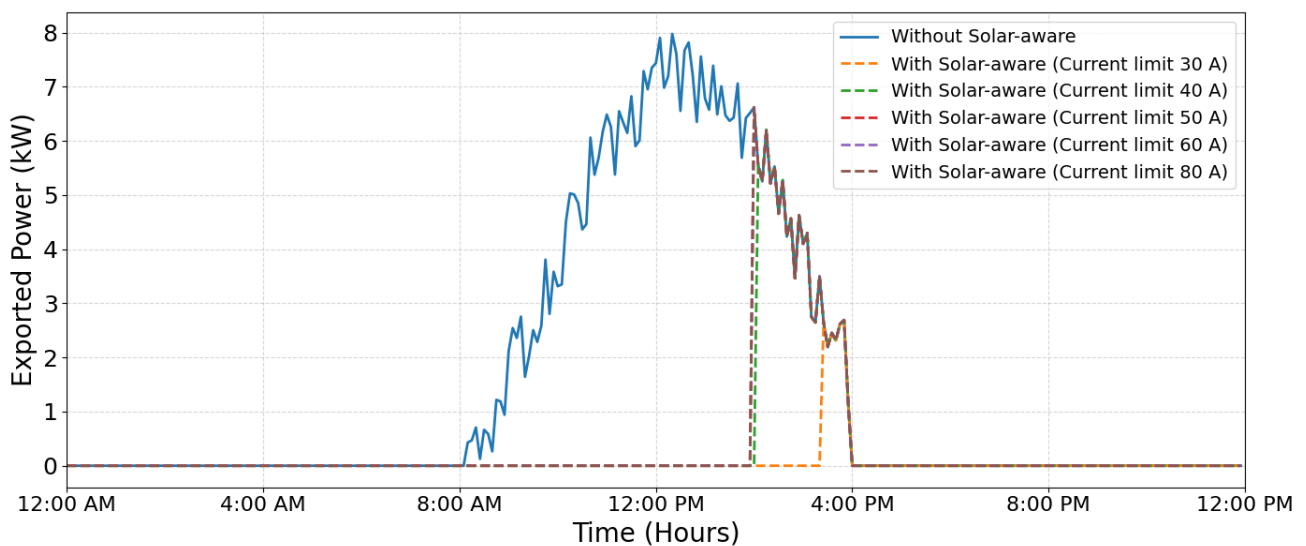


Figure 3.7: Solar-export to the grid under varying panel current limits.

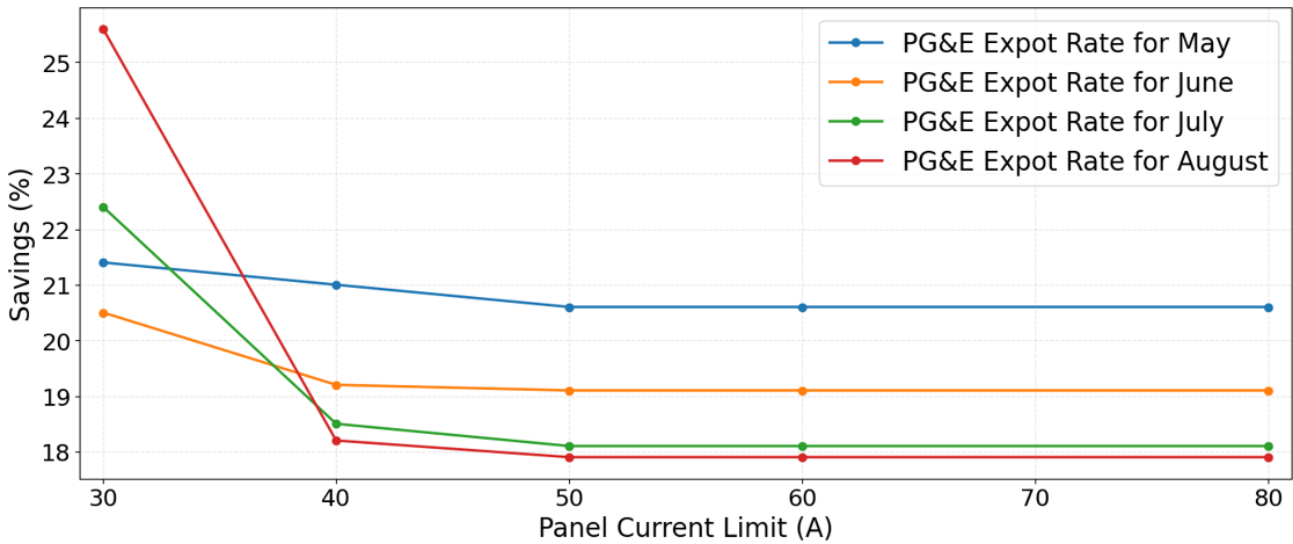


Figure 3.8: TOU cost savings under PG&E export rates for varying panel current limits during summer.

Additional key metrics for solar-aware algorithm are provided in Table 3.4. The results confirm that local solar utilization increases dramatically under all controlled cases, with up to 98% utilization at 30 A panel current limit. Correspondingly, solar-export to the grid drops from 55% to as low as 2%. Under NEM 3.0, using solar PV on local load is economically beneficial most of the cases. So, lowering the solar export to the grid can improve the economic value of self-generated solar. Notably, up to 50% of the EV charging load is met directly by solar at the lowest current limit. Peak load reduction reaches 20% at the lowest current limit with a small increase in charging duration.

Table 3.4: Performance comparison of NeoCharge’s solar-aware algorithm under varying panel current limits

Key Parameter	Without Solar-Aware Algorithm	With NeoCharge Solar-aware algorithm				
		Current Limit 30 A	Current Limit 40 A	Current Limit 50 A	Current Limit 60 A	Current Limit 80 A
Local Solar Utilization (%)	45	98	89	88	88	88
Solar Export to Grid (%)	55	2	11	12	12	12
EV Load Served by Solar (%)	0	50	42	41	41	41
Peak Load Reduction (%)	0	20	6	0	0	0
Charging Time (hr)	6	7.33	6.08	6	6	6



3.4 Case 4: Impact of Start Time of EV Charging Window

This case study investigates the effect of varying EV charging start times on key performance metrics. The objective is to determine optimal scheduling strategies that maximize solar self-consumption and reduce utility costs. Figure 3.9 illustrates the solar-export profiles across five different EV charging start times. As charging is initiated earlier in the day, more of the available solar energy is consumed locally, resulting in reduced exports. The most reduction occurs when charging begins at 10 AM, which aligns closely with the solar production peak.

Figure 3.10 quantifies the energy cost savings achieved under each scenario across four summer months. Charging that begins at 10 AM consistently offers the highest savings, peaking at over 21% in May. As the start time shifts later into the afternoon, savings decline sharply, reflecting missed opportunities to capture midday solar energy.

Table 3.5 summarizes the detailed performance metrics across all tested start times. Charging that begins at 10 AM resulted in the highest solar utilization (95.9%), lowest export (4.1%), and maximum EV load served by solar (46.5%). This scenario also achieved the greatest peak load reduction (18.4%) without increasing total charging time. In contrast, delaying charging to 4 PM significantly reduced local solar use and required longer charging time to complete the charging session, while offering minimal cost benefit.

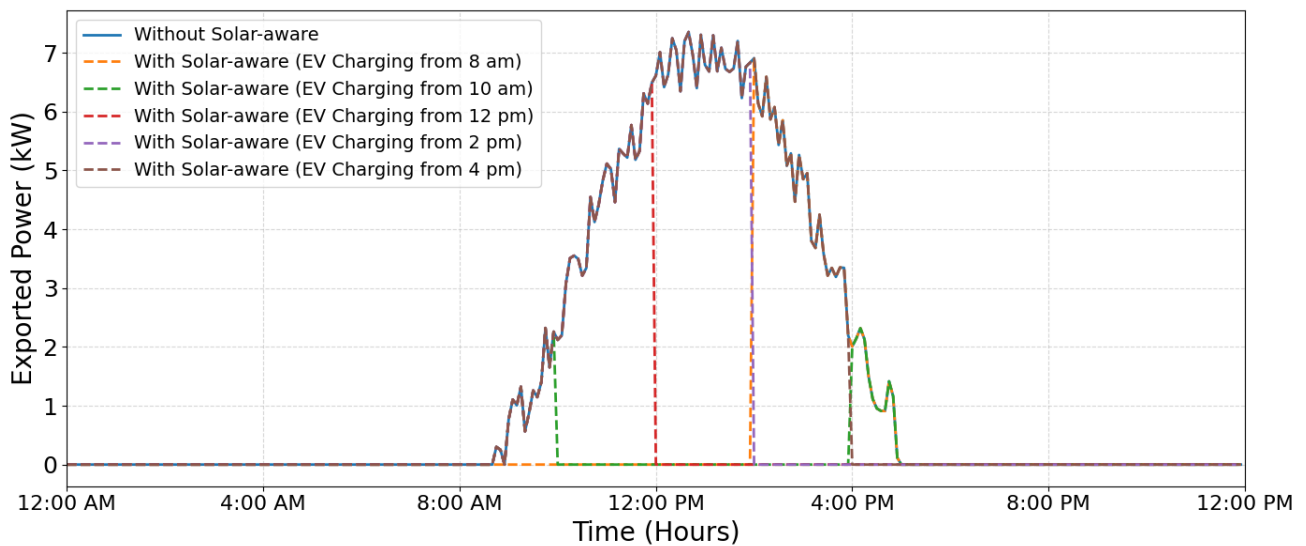


Figure 3.9: Solar-export to the grid under varying start time of EV charging window.

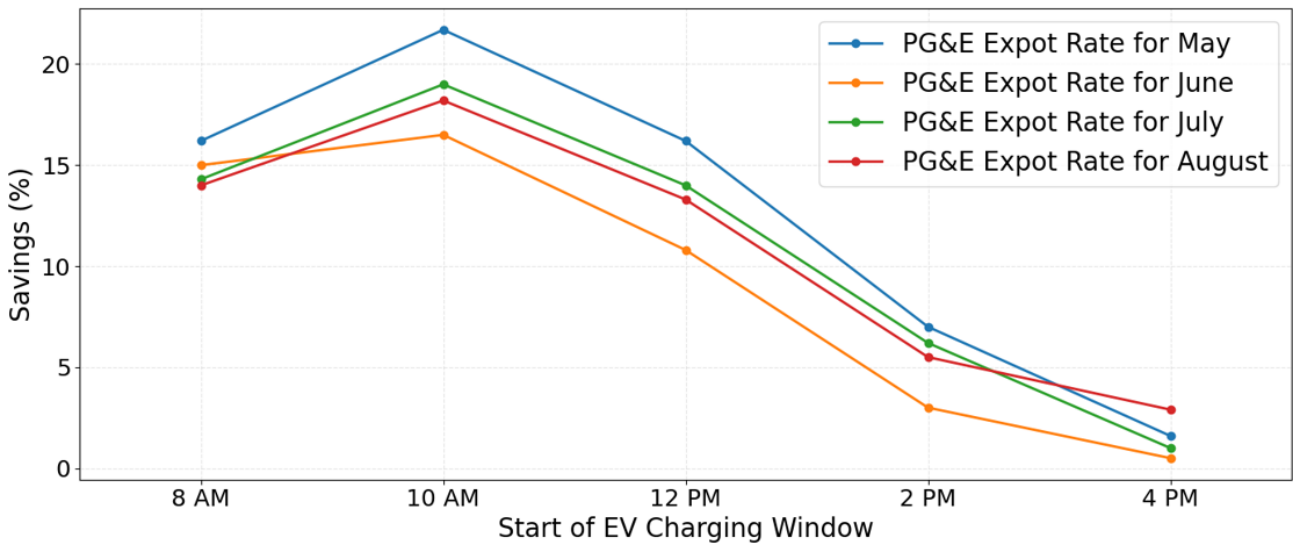


Figure 3.10: TOU cost savings under PG&E export rates for varying start time of EV charging.

Table 3.5: Summary of solar-aware EV charging performance under different charging start times

Key Parameter	Without Solar-Aware Algorithm	With NeoCharge Solar-aware algorithm				
		Charging from 8 am	Charging from 10 am	Charging from 12 pm	Charging from 2 pm	Charging from 4 pm
Local Solar Utilization (%)	48.3	84.0	95.9	84.6	64.3	50.3
Solar Export to Grid (%)	51.7	16.0	4.1	15.4	35.7	49.7
EV Load Served by Solar (%)	0	34.8	46.5	35.4	15.6	2.0
Peak Load Reduction (%)	0	0	18.4	0	0	0
Charging Time (hr)	6	6	6	6.17	7.58	8.25

3.5 Case 5: Impact of Different EVs

This case explores how vehicle-specific charging profiles influence solar-export behavior and savings under the NeoCharge solar-aware algorithm. The goal is to quantify how different battery capacities and charging power needs affect solar utilization, grid impact, and economic return under PG&E’s NEM 3.0 export rates. Key specifications for this study:

- Simulations are conducted for three EV types: Tesla Model 3, Rivian R1T, and Nissan Leaf
- Charging begin at 10 AM for each EV, aligned with solar production ramp-up
- Capacities of these EVs are 82 kWh, 135kWh, and 62 kWh, respectively

Figure 3.11 shows the solar-export to the grid for all three EVs with solar-aware algorithm. All

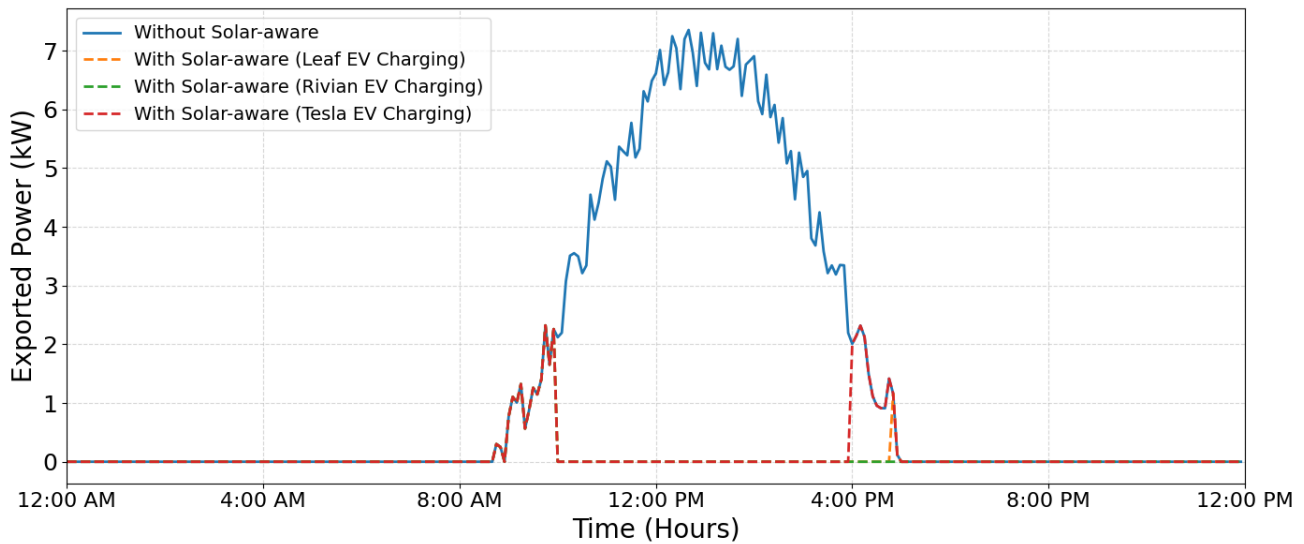


Figure 3.11: Solar-export to the grid with NeoCharge solar-aware optimization for three EV models

three EVs significantly reduce midday solar export, especially during the period between 10 AM and 3 PM. The Leaf, with the smallest capacity, absorbs more solar power early on, while the Rivian and Tesla extend charging further into the afternoon.

Savings from the solar-aware algorithm vary across both EV type and month. Table 3.6 shows that the Nissan Leaf consistently achieves the highest cost savings, up to 26.1% in May, due to its smaller charging demand. The Rivian R1T, being the largest EV in the comparison, results in the lowest cost savings due to higher charging energy.

Tables 3.7 summarizes key performance metrics for each EV. All three vehicles show high solar utilization, more than 95% and reduced solar-export with the Leaf having the highest EV load served by solar due to its lower capacity. The Tesla Model 3 achieves moderate savings with the greatest peak load reduction of around 18%. The Rivian achieves highest local solar utilization but no peak load reduction due to its high capacity.

Table 3.6: Monthly savings for each EV model under PG&E NEM 3.0 export rates with NeoCharge optimization

PG&E Export rate (Month)	Savings with NeoCharge Solar-aware algorithm (%)		
	Tesla Model 3	Rivian R1T	Nissan Leaf
May	21.7	15.0	26.1
June	16.5	10.7	19.3
July	19.0	12.9	22.7
August	18.2	12.4	21.7

Table 3.7: Key performance metrics comparing three EVs under solar-aware charging

Key Parameter	Without Solar-Aware Algorithm	With NeoCharge Solar-aware algorithm		
		Tesla Model 3	Rivian R1T	Nissan Leaf
Local Solar Utilization (%)	48.3	95.9	98.0	97.8
Solar Export to Grid (%)	51.7	4.1	2.0	2.2
EV Load Served by Solar (%)	0	46.5	29.4	63.9
Peak Load Reduction (%)	0	18.4	0	6.6

3.6 Case 6: Multiple EV Charging Scenario

In this scenario, NeoCharge’s algorithm is evaluated under a high-load condition involving three electric vehicles (Tesla, Rivian, and Nissan Leaf) and a residential solar PV system. The aim is to assess how well NeoCharge manages simultaneous EV charging while maximizing solar utilization and minimizing grid impact under NEM 3.0 pricing. The input parameters of different EVs for the algorithm are provided in Table 3.8.

NeoCharge coordinates all three EVs charging schedules with priority order with and without solar-aware algorithm. Figure 3.12 represents the baseline (non-EV) load, available solar power, and power drawn from the grid. NeoCharge minimizes grid consumption during daylight by aligning EV charging with solar availability, while managing transitions before and after solar hours to avoid demand spikes.

Figure 3.13 shows individual EV charging patterns.

Table 3.8: Input parameters for different EVs

EV Name	Battery Capacity (kWh)	Initial SoC (%)	Final SoC (%)	Charge Time	Priority Order
Tesla	82	10	90	7 pm - 7am	1
Rivian	135	30	85	9 am - 5 pm	2
Leaf	62	50	90	5 pm - 11 pm	3

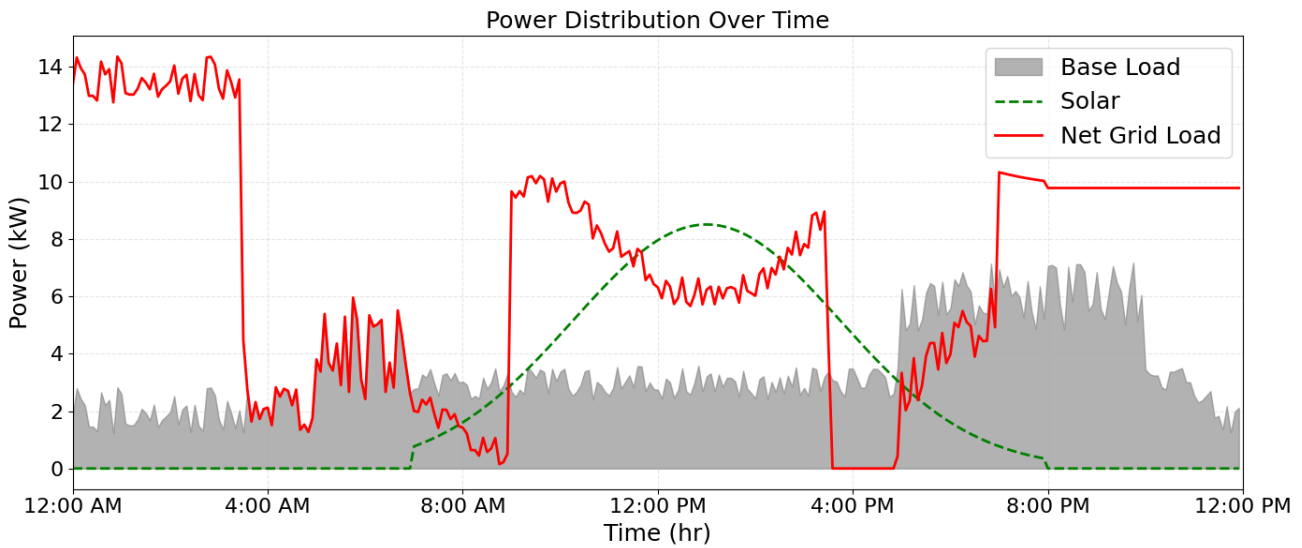


Figure 3.12: Net load and solar generation with NeoCharge’s solar-aware charging algorithm for Case 6.

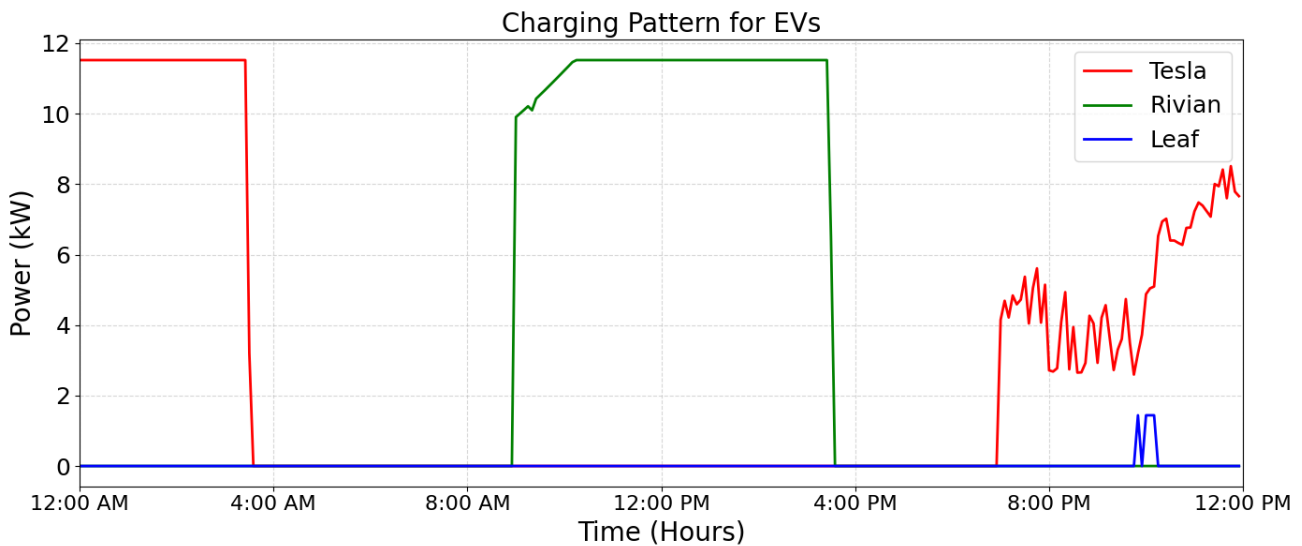


Figure 3.13: Individual EV charging pattern for Case 6.

NeoCharge effectively staggers the charging times based on available solar output and current limits, avoiding overlapping demand and peak transformer loading. That is the reason behind leaf’s low charging. Figure 3.14 displays the impact on solar-export of solar-aware NeoCharge algorithm. Solar is utilized most of the time for charging EVs. With the solar-aware algorithm enabled, solar is only exported to the grid between 4:00 PM and 6:00 PM, during which no EVs are available for charging; at all other times, the algorithm successfully aligns EV charging with solar generation to maximize on-site solar utilization.

Table 3.9 presents the performance comparison with and without NeoCharge’s solar-aware optimization. EV load served by solar increases from 0 kWh to 24.35 kWh which is 17.28% of the total

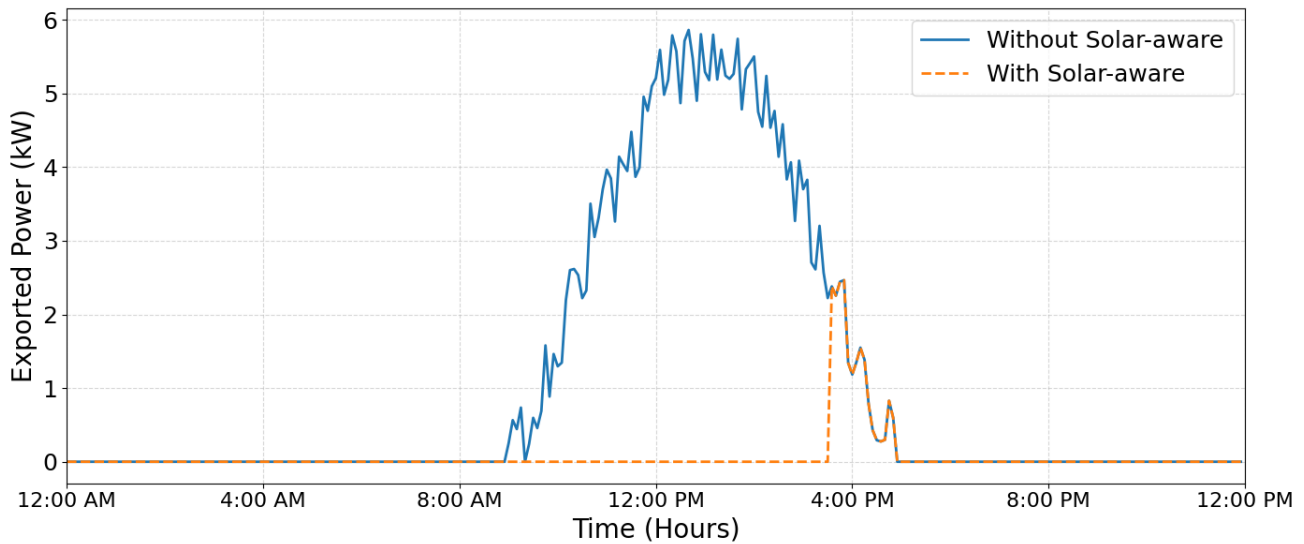


Figure 3.14: Solar power exported to the grid, with and without NeoCharge’s solar-aware algorithm.

EV load. Solar-export drops from 26.00 kWh to 1.65 kWh, a 93.6% reduction and solar utilization increases from 31.22 kWh to 55.57 kWh, a 43.80% increase in local solar utilization. Utilizing solar for EV charging decreases TOU cost for both May and August by 10.30% and 8.44%, respectively under NEM 3.0. Peak load occurs at 12:55 am for both cases.

The results from the solar-aware case studies show that the NeoCharge optimization algorithm can enhance residential solar utilization while reducing overall energy costs. By aligning EV charging schedules with periods of high solar generation, the algorithm has the capability to minimize midday export to the grid and maximizes local consumption. The analysis shows that the algorithm might provide up to 26% in savings under PG&E export compensation rate during summer. However, the set point for panel current limit, residential load profile, and EV charging time will play an important role in achieving that amount of savings.

Table 3.9: Results for multi-EV solar-aware charging using NeoCharge

Key Parameter	Without Solar-aware NeoCharge	With Solar-aware NeoCharge
Tou Cost (\$) with Nem 3 for May	53.35	47.85
Tou Cost (\$) with Nem 3 for August	52.09	47.69
Peak Load (kW)	14.34	14.34
Load Factor (%)	37.60	37.60
Solar Produced (kWh)	57.23	57.23
Solar utilization (kWh)	31.22	55.57
Solar export to grid (kWh)	26.00	1.65
EV load served by solar (kWh)	0	24.35

Chapter 4

Conclusion

This report demonstrates the effectiveness of the NeoCharge optimization algorithm in managing residential EV charging across a wide range of charging scenarios. Across multiple test cases, the algorithm consistently demonstrated its ability to shift EV charging loads away from peak grid periods. This could lead to reductions in peak household demand by up to 45% and improvements in system load factor up to 20%. These benefits are especially noticeable when the algorithm operates under lower panel current limits, which allow for finer control over EV load distribution, particularly during on-peak hours. The results also show NeoCharge's could reduce cost for residential electricity cost up to 17% considering EV on-peak charging scenario with lower set points for panel current limit.

The integration of NeoCharge with solar-aware algorithm further enhances its performance by increasing local solar utilization and reducing midday solar-export to the grid. In some scenarios, local solar utilization reaches approximately 98% and solar export to the grid is reduced to only 2%. When EV is available for charging during the day, more than 50% of EV energy demand is directly served by residential solar power. The results demonstrate the NeoCharge's solar-aware algorithm's potential in achieving up to 26% reduction in energy costs under NEM 3.0 policy, compared to normal charging scenarios where EVs are charged without solar-aware algorithm.

Apart from cost savings, NeoCharge's algorithms might be able to alleviate peak loading on local transformers and feeders, reducing the risk of thermal stress. Additionally, The analysis show NeoCharge's algorithms can potentially provide support to the grid by flattening residential demand curves, improving load factor, and utilizing distributed renewable generation locally.