

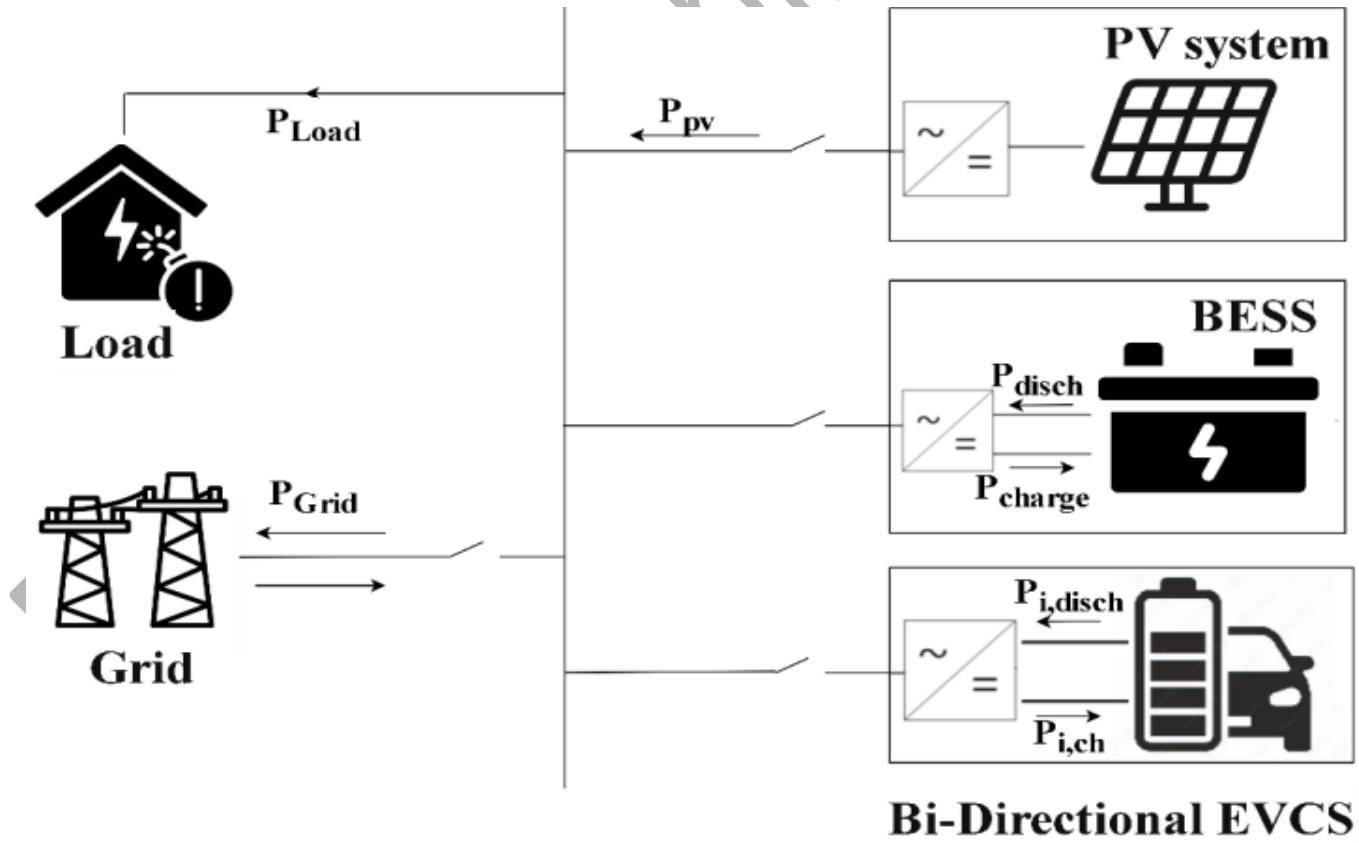
# Performance Improvement of Utilities Power Grids with Virtual Power Plant Integration

## 1.1 Research Objectives

The study aims to develop a smart energy management system (EMS) for grid-connected Virtual Power Plants (VPPs) that efficiently coordinates PV generation, loads, battery energy storage system (BESS), and electric vehicles (EVs). It integrates advanced forecasting using AI-based models to improve predictions of renewable generation, load demand, EVs arrival/departure times, and electricity prices, and uses a Mixed-Integer Non-Linear Programming optimization framework to balance economic and technical objectives. The framework enhances PV integration, enables prosumers market participation, supports bidirectional EV-grid interaction (G2V/V2G), and evaluates trade-offs between cost minimization and grid-support.

## 1.2 VPP Component Modelling

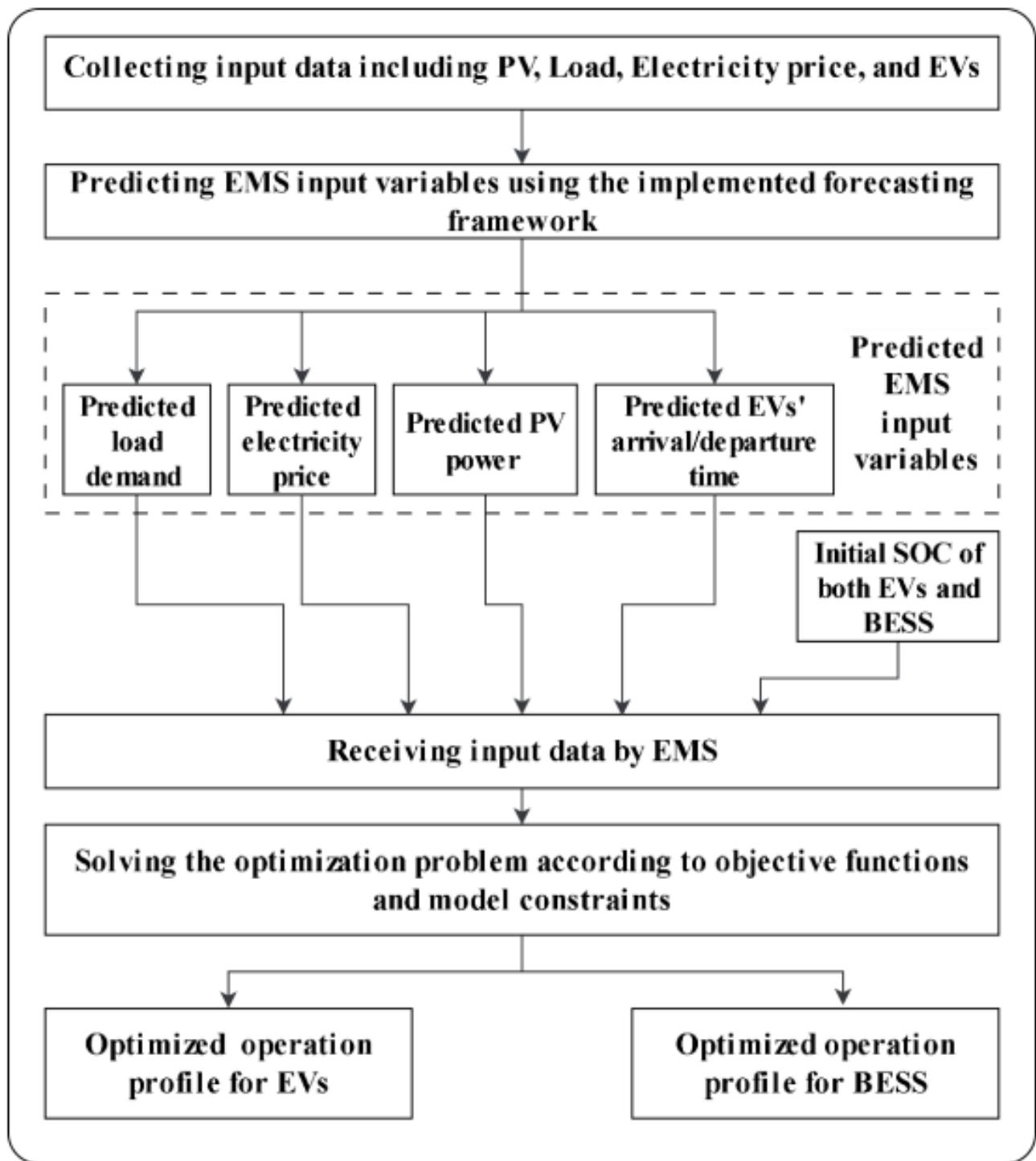
The single-line diagram of the proposed system is produced with the power flows.



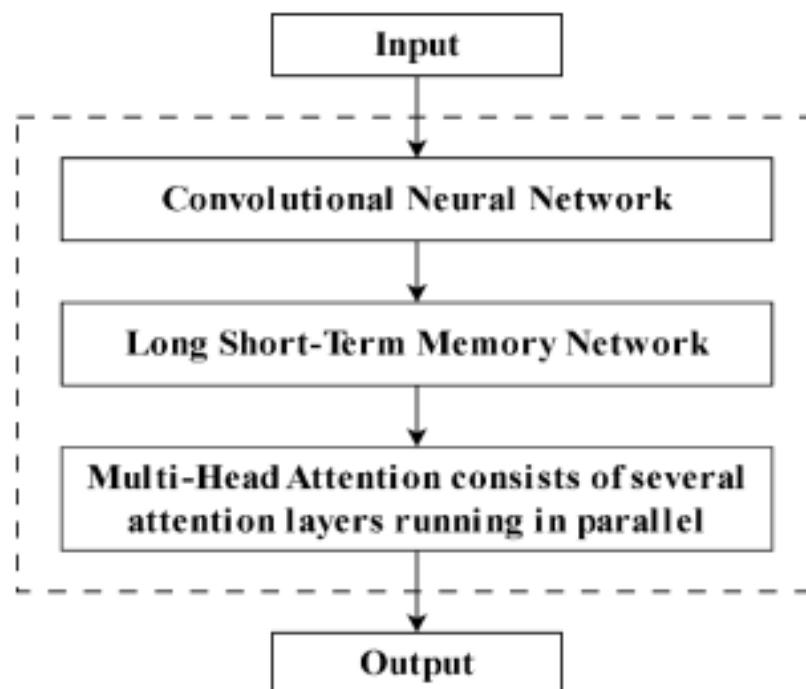
*Fig. 3-1 Structure of the case study [69]*

$$\begin{aligned}
 P_{grid}[t] + P_{pv}[t] + P_{BESS}^{dis}[t] * \eta_{inv}^{BESS} + \sum(P_{EV,i}^{dis}[t] * \eta_{inv}^{EV,i}) = P_{load}[t] + \\
 \frac{P_{BESS}^{ch}[t]}{\eta_{inv}^{BESS}} + \sum\left(\frac{P_{EV,i}^{ch}[t]}{\eta_{inv}^{EV,i}}\right)
 \end{aligned} \quad (3-1)$$

### 1.2.1 EMS Architecture



*Fig. 3-4 Proposed EMS architecture within the VPP configuration*

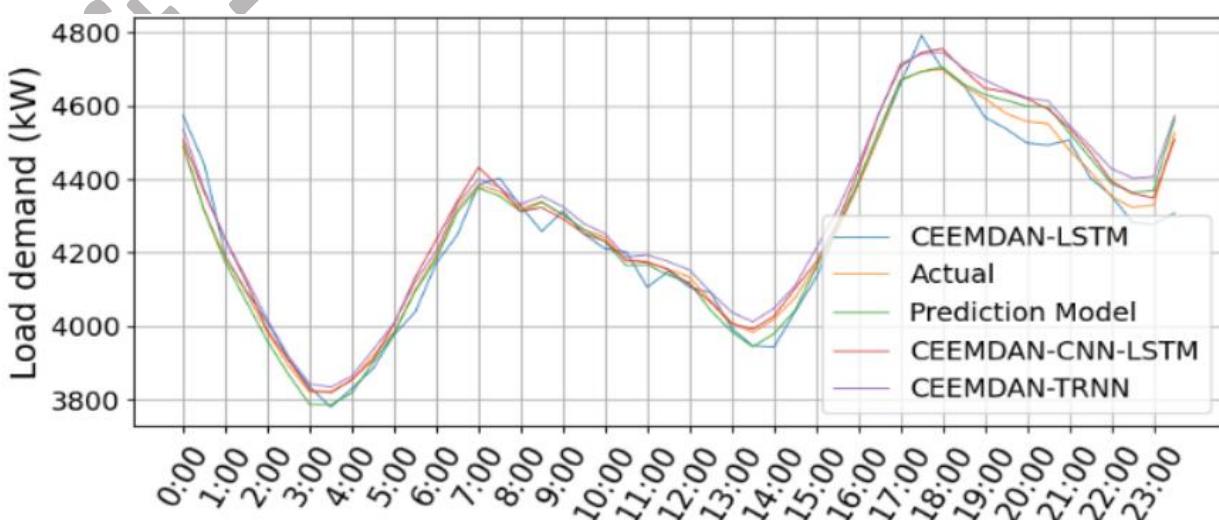


*Fig. 4-18 CNN-LSTM with Multi-Head Attention architecture*

### 1.3 Forecasting of EMS Input Variables

*Table 4-15 Evaluation metrics of the predicted load demand*

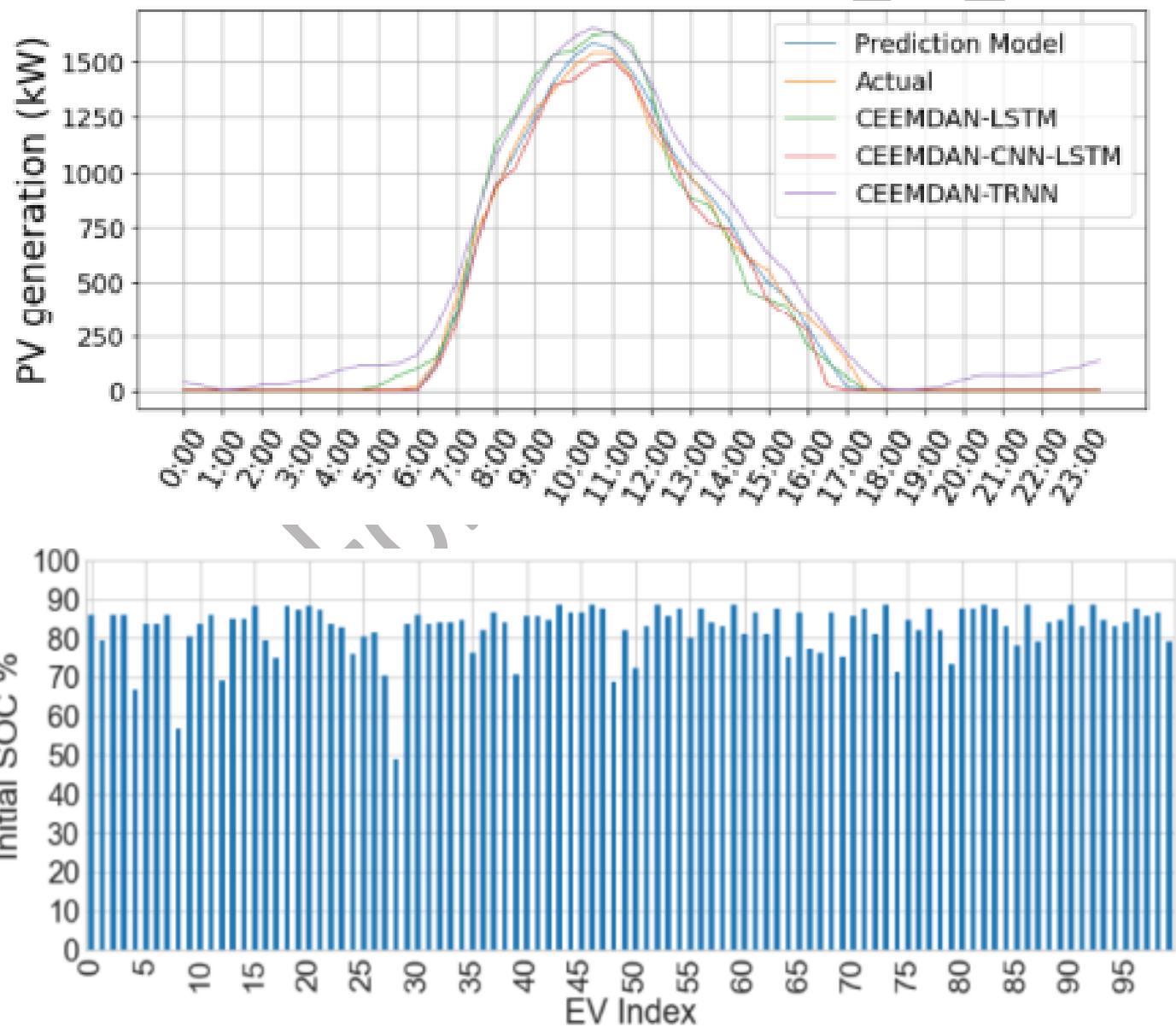
	LSTM	TRNN	CNN-LSTM	Prediction Model
<b>MAPE (%)</b>	0.85	0.83	0.58	0.45
<b>RMSE</b>	53.32	42.15	32.03	24
<b>MAE</b>	36.39	36.32	25.71	4.38
<b>R<sup>2</sup> (%)</b>	95.35	97.22	98.42	99.13



*Fig. 4-30 Predicted load demand compared with validation models*

*Table 4-17 Evaluation metrics of the predicted PV generation*

	<b>LSTM</b>	<b>TRNN</b>	<b>CNN-LSTM</b>	<b>Prediction Model</b>
<b>RMSE</b>	<b>79.40</b>	<b>99.22</b>	<b>60.82</b>	<b>40.60</b>
<b>MAE</b>	<b>49.82</b>	<b>84.45</b>	<b>33.84</b>	<b>22.76</b>
<b>R<sup>2</sup> (%)</b>	<b>98.05</b>	<b>96.85</b>	<b>98.64</b>	<b>99.44</b>

*Fig. 5-4 Estimated SOC for each EV upon arrival as input to the EMS*

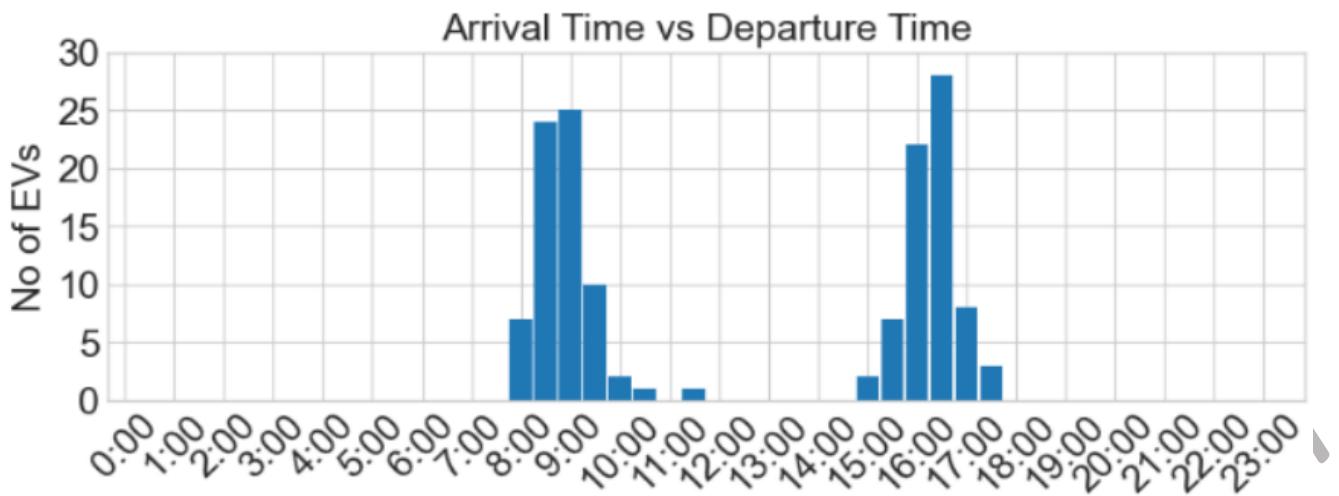


Fig. 5-5 Histogram of predicted EV arrival and departure times as input to the EMS

## 1.4 Case Studies

- **Base Case:** EVs only charge during their parking time, regardless of the electricity price, which slightly increased stress on the utility grid
- **Case 1:** Minimization of Power Imported from the Grid
- **Case 2:** Minimization of Electricity Cost
- **Case 3:** Cost Minimization with Peak Shaving Constraint
- **Case 4:** Multi-Objective Optimization (Case1 + Case2)

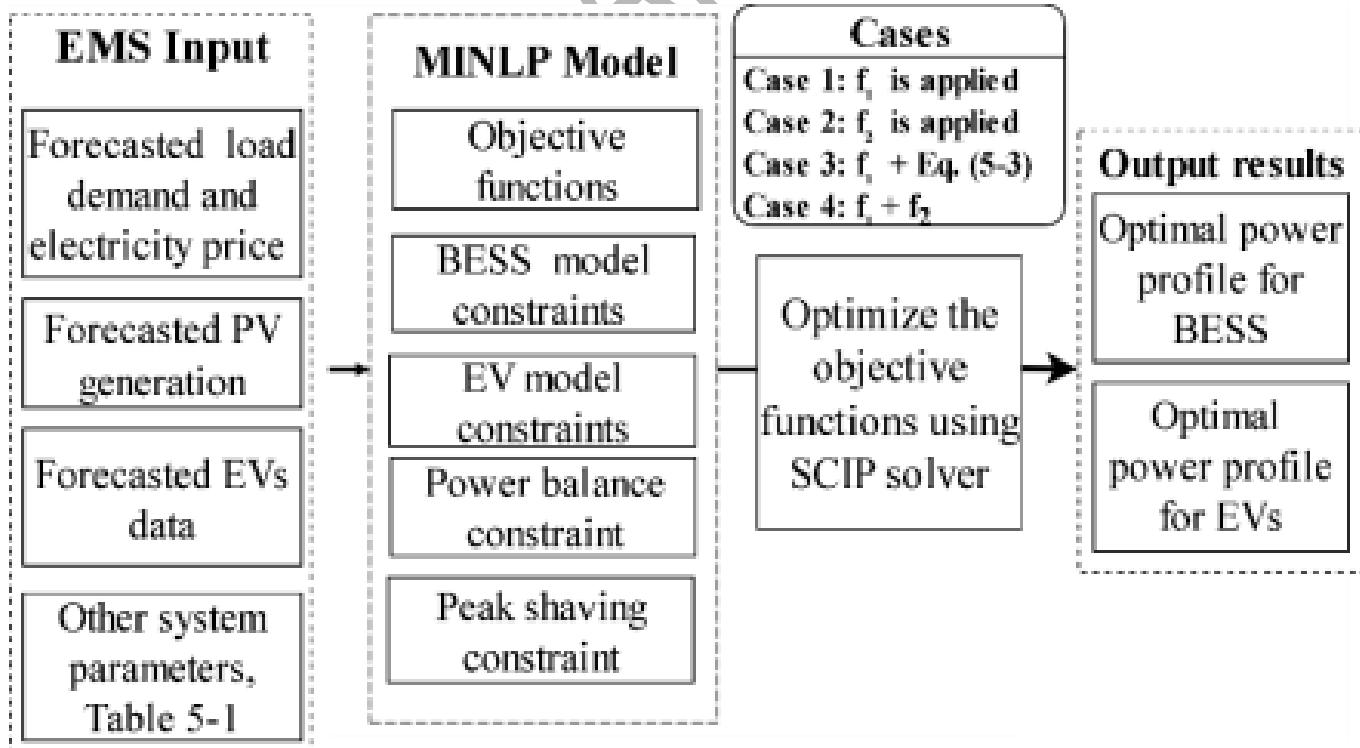
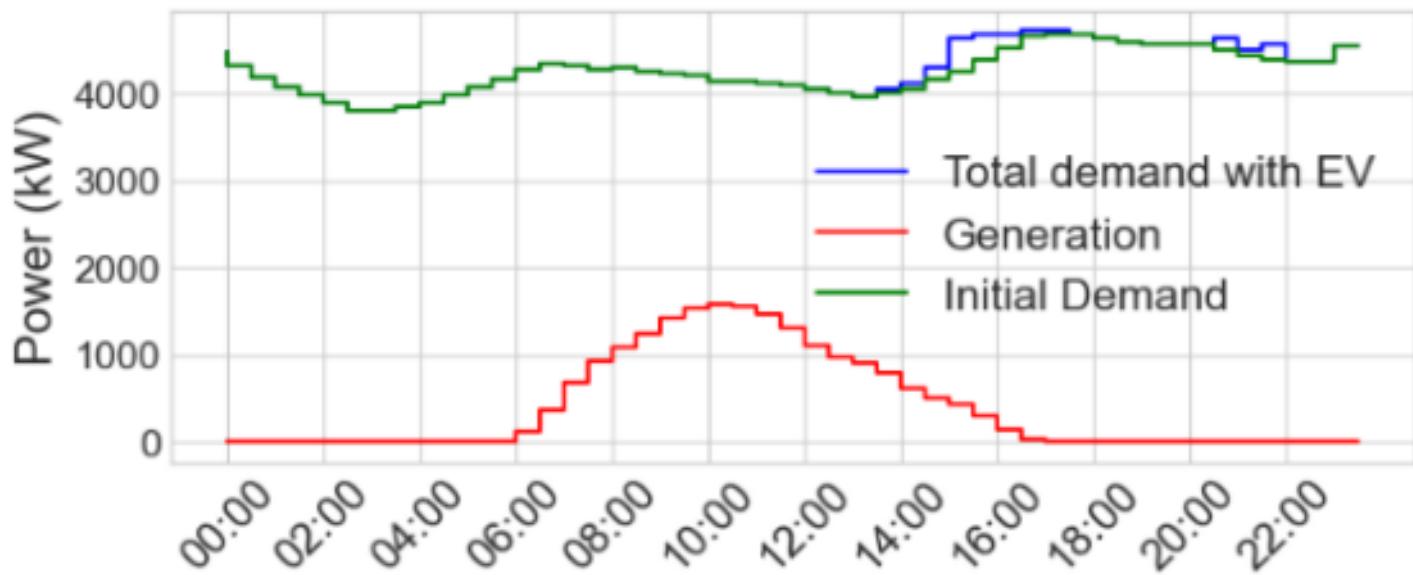
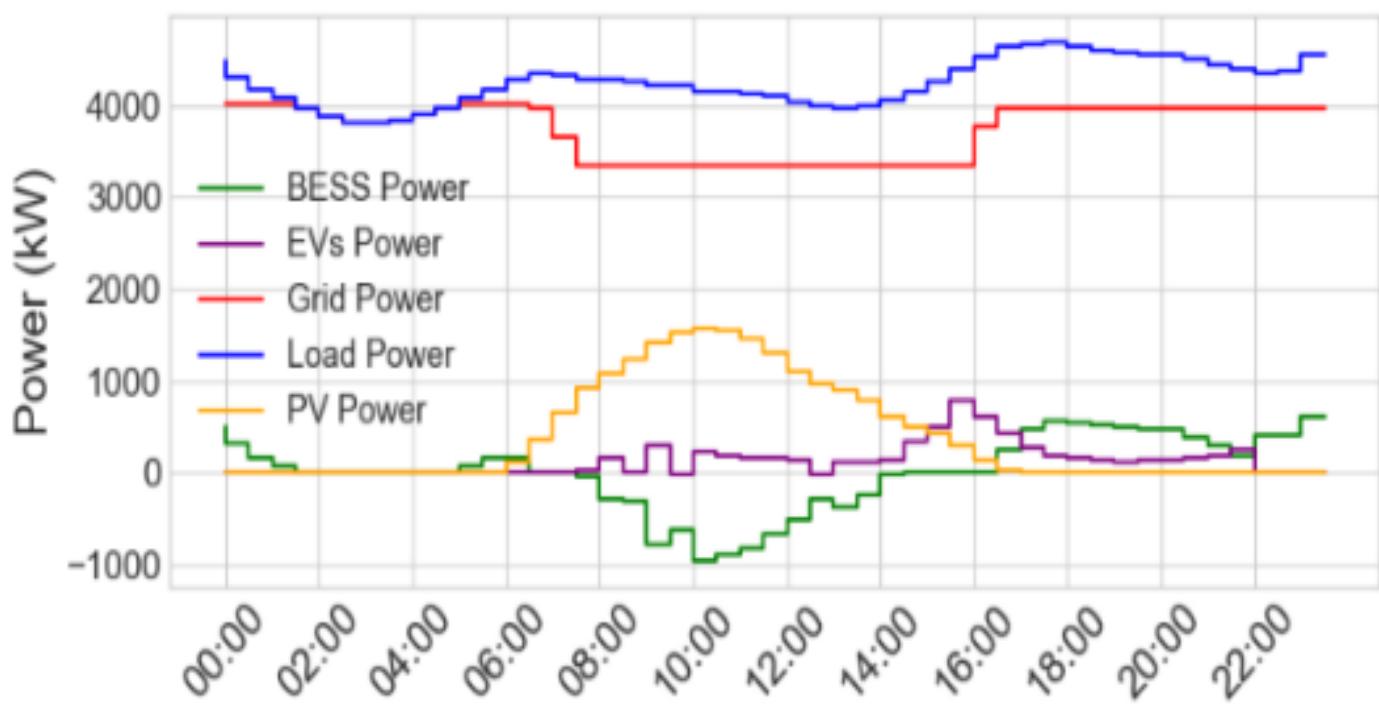


Fig. 5-7 Optimization framework within the EMS architecture



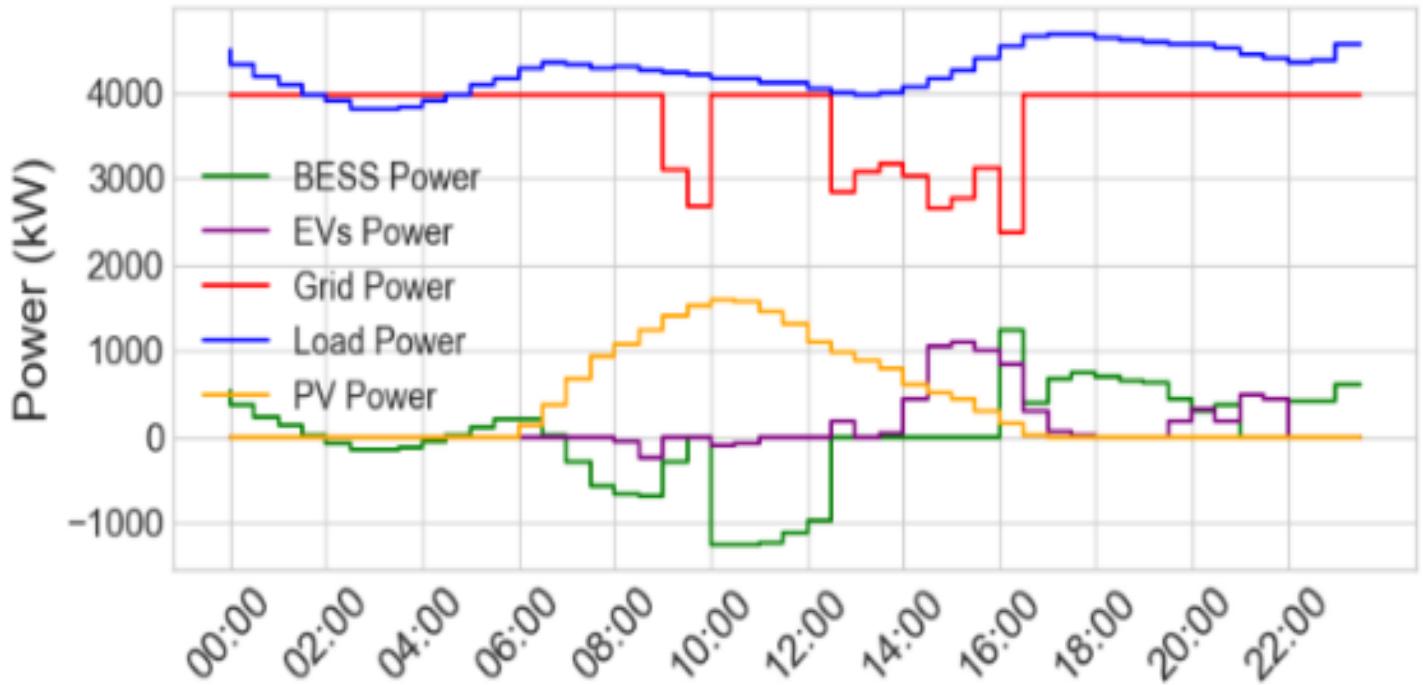
*Fig. 5-8 Initial demand and generation in the base case*



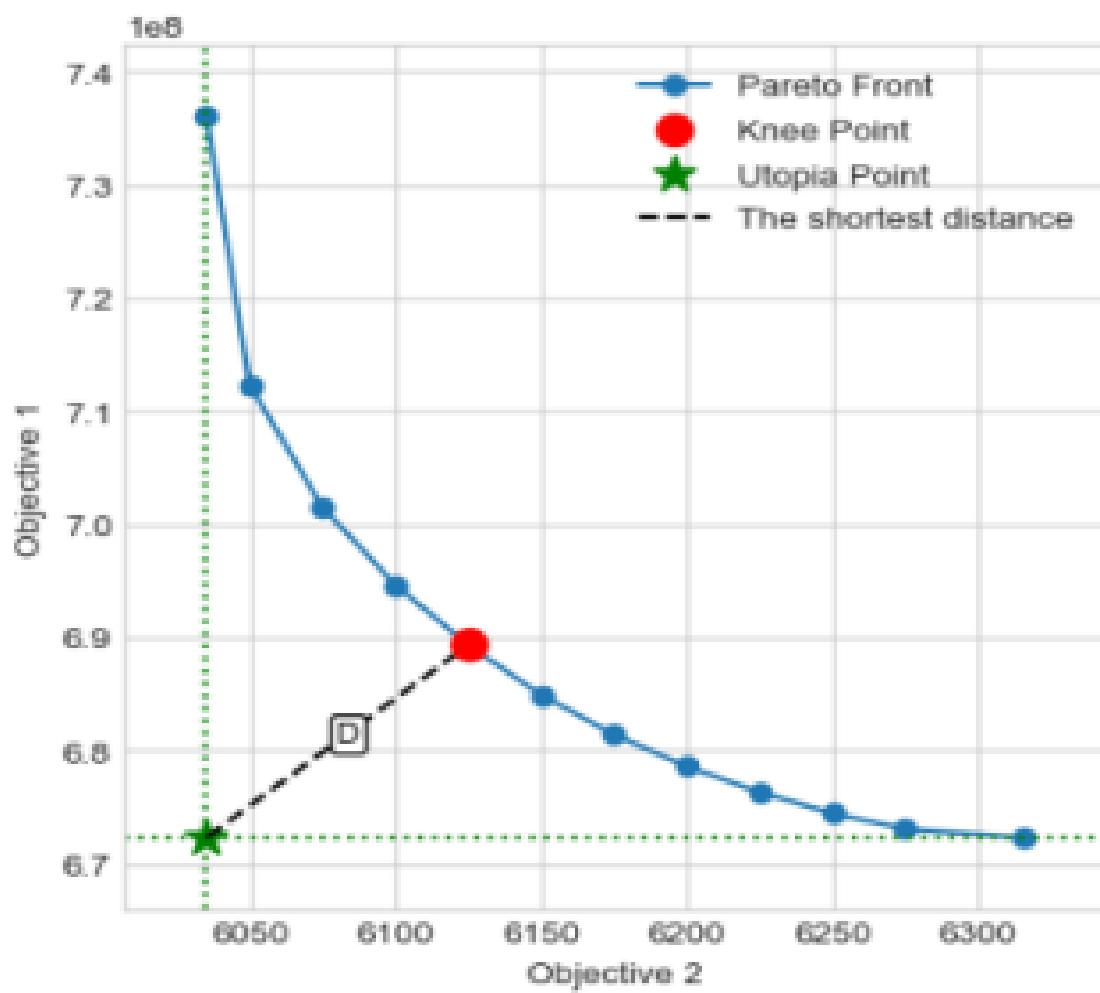
*Fig. 5-10 Overview of EMS performance in Case 1*



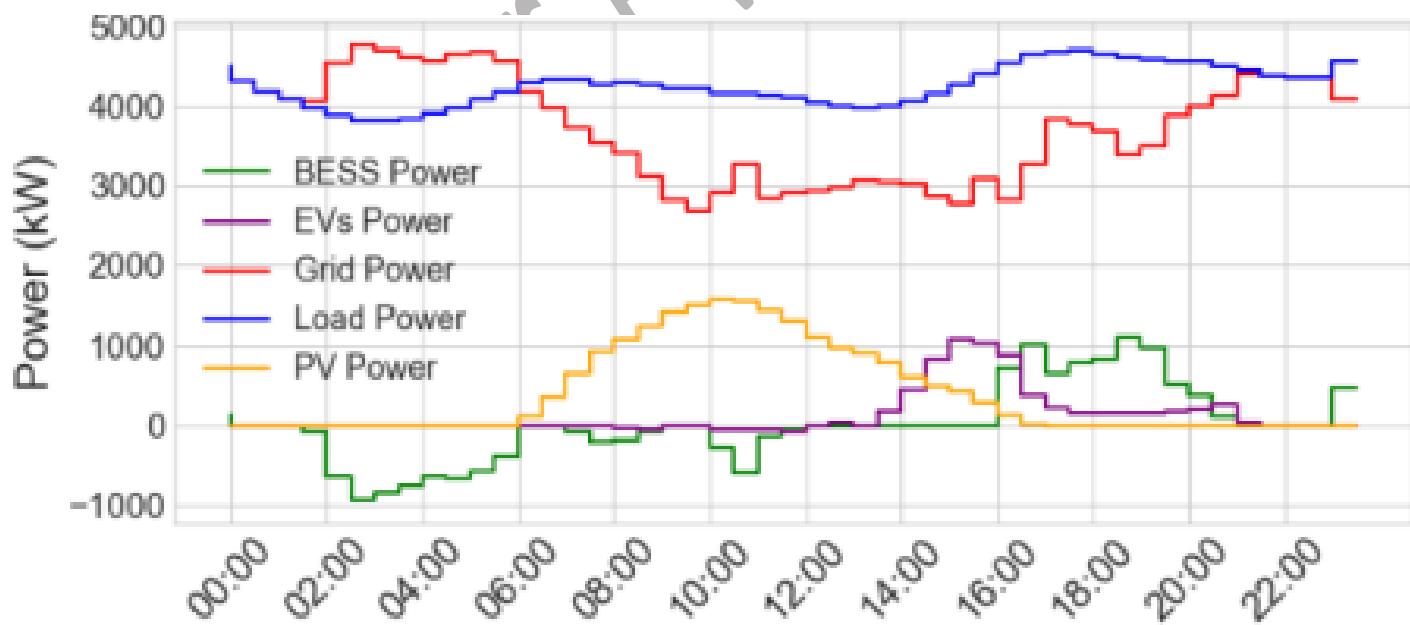
*Fig. 5-15 Scheduled power for the BESS and EVs in Case 2*



*Fig. 5-12 Overview of EMS performance in Case 3*

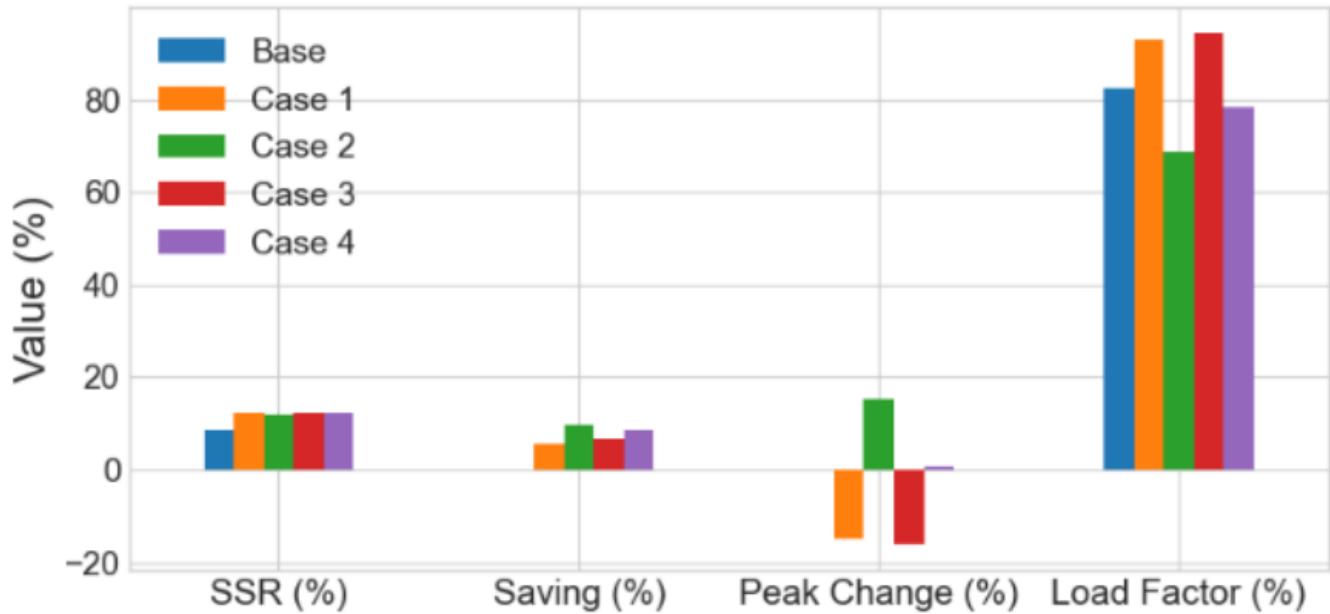


*Fig. 5-6 Pareto front showing knee and utopia points for Case 4*



*Fig. 5-13 Overview of EMS performance in Case 4*

## 1.5 Results



*Fig. 5-30 Comparison of key performance metrics*

## 1.6 Code Snippets

```
demand_df=pd.read_csv(r"C:\Users\Basel\Desktop\Optimization Model V13\Input data\Day-Ahead-Load.csv",index_col=[0])
```

```
price_df=pd.read_csv(r"C:\Users\Basel\Desktop\Optimization Model V13\Input data\Day-Ahead-Price.csv",index_col=[0])
```

```
vpp = ConcreteModel()
opt = SolverFactory('scip', executable=r'C:\Program Files\SCIP Opt Suite 9.2.2\bin\scip.exe')

def Balance_Constraint(vpp, t):
    EVs_Sum_Discharging = sum((getattr(vpp, f'EV_Discharge_Power_{i}')[t] * EV_INV_EFFICIENCY ) for i in vpp.SetIndex)
    EVs_Sum_Charging = sum((getattr(vpp, f'EV_Charge_Power_{i}')[t] / EV_INV_EFFICIENCY ) for i in vpp.SetIndex)
    return vpp.Grid[t] + vpp.PV[t] +(vpp.BESS_Discharge_Power[t] * BESS_INV_EFFICIENCY )
+ EVs_Sum_Discharging == vpp.Load[t]+(vpp.BESS_Charge_Power[t] / BESS_INV_EFFICIENCY )+ EVs_Sum_Charging

vpp.Balance_Constraint = Constraint(vpp.Period, rule=Balance_Constraint)

vpp.BESS_Energy = Var(vpp.Period, bounds=(BESS_MIN_ENERGY, BESS_MAX_ENERGY))
vpp.BESS_SOC = Var(vpp.Period, bounds=(BESS_MIN_SOC, BESS_MAX_SOC))
vpp.BESS_Charge_Power = Var(vpp.Period, bounds=(0,BESS_MAX_CH_POWER))
vpp.BESS_Discharge_Power = Var(vpp.Period, bounds=(0,BESS_MAX_DIS_POWER))
vpp.BESS_Discharge_State=Var(vpp.Period,domain=Binary)
vpp.BESS_Charge_State=Var(vpp.Period,domain=Binary)
```

```

def BESS_Energy_Constraint(vpp, t):
    if t == vpp.Period.first():
        return vpp.BESS_Energy[t] == BESS_INITIAL_ENERGY
    return vpp.BESS_Energy[t] == (vpp.BESS_Energy[t-1]
                                  + (vpp.BESS_Charge_Power[t-1] * dt * BESS_CH EFFICIENCY )
                                  - (vpp.BESS_Discharge_Power[t-1] * dt / BESS_DIS EFFICIENCY))

for i in vpp.SetIndex:

    setattr(vpp, f'EV_Energy_{i}', Var(vpp.Period, bounds=(EV_MIN_ENERGY, EV_MAX_ENERGY)))
    setattr(vpp, f'EV_SOC_{i}', Var(vpp.Period, bounds=(EV_MIN_SOC, EV_MAX_SOC)))
    setattr(vpp, f'EV_Charge_Power_{i}', Var(vpp.Period, bounds=(0, EV_MAX_CH_POWER)))
    setattr(vpp, f'EV_Discharge_Power_{i}', Var(vpp.Period, bounds=(0, EV_MAX_DIS_POWER)))
    setattr(vpp, f'EV_Discharge_State_{i}', Var(vpp.Period, domain=Binary))
    setattr(vpp, f'EV_Charge_State_{i}', Var(vpp.Period, domain=Binary))

def EV_Energy_Constraint_Rule(vpp, t):
    if t == vpp.Period.first():
        return getattr(vpp, f'EV_Energy_{i}')[t] == evs_initial_energy_df.loc[i,"Initial_Energy"]
    return getattr(vpp, f'EV_Energy_{i}')[t] == (
        getattr(vpp, f'EV_Energy_{i}')[t - 1]
        + (getattr(vpp, f'EV_Charge_Power_{i}')[t - 1] * dt * EV_CH EFFICIENCY)
        - (getattr(vpp, f'EV_Discharge_Power_{i}')[t - 1] * dt / EV_DIS EFFICIENCY))

def Grid_Power(vpp,t):
    gridPower = sum(vpp.Grid[t] ** 2 for t in vpp.Period)
    return (1e-1) * gridPower

def Grid_Cost(vpp,t):
    gridCost = sum(vpp.Grid[t] * df.price[t] * dt for t in vpp.Period)
    return gridCost

--- -- -
UTH=3965
FOR
X X

def UTH_Constraint(vpp, t):
    return abs(vpp.Grid[t]) <= UTH

#vpp.UTh_Con = Constraint(vpp.Period, rule=UTH_Constraint)
#vpp.Epsilon_Constraint = Constraint(vpp.Period, rule=epilson_constraint)
vpp.objective = Objective(rule=Grid_Power , sense=minimize )
#vpp.objective = Objective(rule=Grid_Cost , sense=minimize)

SSR = (1 - (df['Grid'] * dt).sum() / (df['Load'] * dt).sum()) * 100
Bill = df['Cost'].sum()
Peak = df['Grid'].max()
Saving = abs((Bill - Base_Bill) / Base_Bill) * 100
Load_Factor = df['Grid'].mean() / df['Grid'].max() * 100
SCR = ((df['PV'] * dt).sum() - abs((df.loc[df['Grid'] < 0, 'Grid'] * dt).sum()) / (df['PV'] * dt).sum()) * 100
Peak_Reduction = (Peak - Base_Peak) / Base_Peak * 100

```

- **Used Tools**

- **Python** – for coding, data analysis, and model implementation
- **Pyomo** – for modelling optimization problems
- **SCIP** – for solving optimization problems
- **Pandas & NumPy** – for data manipulation and numerical calculations
- **Matplotlib & Seaborn** – for visualization of results and analysis
- **Machine learning libraries:** Keras, TensorFlow, and scikit-learn.

Draft - For Application Only