SAMA : Solar Alone Multi-objective Advisor

Modified: November 9th, 2023 by Seyyed Ali Sadat

SAMA (Solar Alone Multi-objective Advisor) is an open-source (GNU GPL v3) energy system optimizer and analyzer mainly concentrated on stand-alone off-grid solar photovoltaic (PV)-based renewable energy systems (RES). SAMA allows for hybrid systems in locations that need a form of non-battery backup generation. Using SAMA, users can find the optimum size of a hybrid energy system for their property based on the electric load profile and meteorological data (irradiation, temperature and wind speed). Users are able to access economic data for their optimum energy system as the results of SAMA optimization and calculations. SAMA is developed in **Python 3.9** using the *NumPy, Numba, time, pandas, math, matplotlib and seaborn*.

SAMA files:

- ✓ **Input_Data.py:** The input data for simulations are defined inside this file.
- ✓ **swarm.py:** In this file, the optimization algorithm which particle swarm optimizer (PSO) code is written.
- ✓ **Fitness.py:** The file including cost calculations and fitness function for optimizer.
- ✓ **EMS.py:** Energy management strategy has been implemented inside this file.
- ✓ **Battery_Model.py:** Chemical battery models are defined inside this file.
- ✓ **calcFlatRate.py, calcMonthlyRate.py, calcMonthlyTieredRate.py, calcSeasonalRate.py, calcSeasonalTieredRate.py, calcTieredRate.py, and calcTouRate.py**: Electric Utility billing schemes are defined in the files above

1. PSO algorithm

The optimizer for SAMA is a particle swarm optimizer (PSO). Full concepts of optimization are discussed in section 4. It is one of the bio-inspired algorithms that seeks to enhance objective function by using a population of potential solutions, here referred to as particles, and moving them across the search space in accordance with a straightforward mathematical formulas (Eq.1 and Eq.2) over the particle ith position in iteration t (P_i^t) and related velocity (V_i^t¿. In Eq.1, W is inertia weight,c_1 is cognitive constant,c_2 is social constant,U_1^t& $U_2^t$are random numbers, and P_b^t as well asg_b^t refer to personal and global best positions of particle in the ongoing iteration (t). Particles positions are updated in each iteration referred as P_i^{t+1}based on the V_i^{t+1} using Eq.2.

$$V_i^{t+1}=W\,.\,V_i^t+c_1 U_1^t\left(P_{b_1}-P_i^t\right)+c_2 U_2^t\left(g_b^t-P_i^t\right) \quad (1)$$

$$P_i^{t+1}=P_i^t+v_i^{t+1} \quad (2)$$

1.1 PSO parameters

Before the PSO main loop, PSO parameters including maximum number of iterations (MaxIt), population size (nPop),W, c_1 and c_2 should be defined. In SAMA, W considered equals to 1, while c_1 and c_2 are both 2. The PSO pseudo code in Python 3.9 is defined as follows:

Initialize population
For t in 1 to MaxIt DO

For i in 1 to nPop DO

1. Evaluate the fitness of the particle.
2. If the current fitness is better than the particle's best fitness (P_b^t), then update the P_b^t with the current fitness and position.
3. If the current fitness is better than the global best fitness (g_b^t), then update the g_b^t with the current fitness and position.
4. Update the velocity of the particle using Eq.1
5. Update the position of the particle using Eq.2

ENDFOR

6. Record the best cost (global best) and mean cost of the particles.
7. Update the inertia weight by multiplying it with a damping factor.

ENDFOR

1.2 Loading electricity load and metrological Input Data

In the PSO code, there is Loading Data section where all the inputs for optimizations and simulations are loaded from each columns of a file with csv format so called **Data.csv**. The input data are electricity load in kW (Eload) as the first column of the csv file, plane of array irradiance (G) in W as the second column, temperature (T) as the third column, wind speed (Vw) in m/s as the fourth column and the electricity load from previous year in kW (Eload_Previous) as the fifth column. Generic electricity load data for U.S. can be accessed through Openei, a database provided by National Renewable Energy Laboratory (NREL) or users can input their own measured or estimated loads. Meteorological data can be accessed through National Solar Radiation Database (NSRDB).

2. Technical and Economical Input data

To run simulations and optimizations, SAMA needs some sets of inputs. Most of these inputs' values are pre-defined in SAMA and if users are uncertain or do not have any information about them can use these default values. Table.1. lists all default values in the SAMA.

Table.1. Default inputs and their values in SAMA (Defined for U.S.)

Type	Data	Specifications	Value	Source
Meteorological	Irradiation	GHI, DNI, DHI	-	[1]
	Temperature	Hourly temperature data in °C	-	
Load	Residential load	Hourly data for different cities across US	-	[2]

Costs	PV	Total PV system Capital cost per kW	$2950	[3], [4]
		PV module's Capital cost *(18.1% of total PV system capital cost)*	$540	
		PV module's Replacement cost *(18.1% of total PV system capital cost)*	$540	
		Installation cost (per kW) (5.4% of total PV system capital cost)	$160	
		Overhead cost (per kW) (8.8% of total PV system capital cost)	$260	
		Sales and marketing (per kW) (13.6% of total PV system capital cost)	$400	
		Permitting and Inspection (per kW) (7.1% of total PV system capital cost)	$210	
		Electrical BoS (per kW) (12.5% of total PV system capital cost)	$370	
		Structural BoS (per kW) (5.4% of total PV system capital cost)	$160	
		Profit (per kW) (11.5% of total PV system capital cost)	$340	
		Sales tax (per kW) (2.7% of total PV system capital	$80	

		cost)		
		PV O&M cost ($/ year/kW)	$29.49	
	Diesel Generator (DG)	DG Capital cost per kW	$240.45	[5]
		Replacement Cost of DG modules per KW	$240.45	[5]
		Diesel fuel cost per liter	$1.39	[6], [7]
		DG O&M+ running cost ($/op.h)	$0.064	[8]
	Battery (BT)	BT Capital cost per kW	$460	[4], [9], [10]
		Replacement Cost of BT per kWh	$460	[9], [10]
	Inverter	Inverter Capital cost per kW *(14.9% of total PV system capital cost)*	$440	[3]
		Replacement Cost of Inverter Per kW	$440	[3]
	Charge controller	Charger Capital cost (part of PV system)	$149.99	[11]
		Charger Replacement Cost	$149.99	[11]
National Economic rates	Nominal discount rate	For U.S. only	4.5%	[12]
	Expected inflation rate		2%	[13]
Technical data Simulation	General	Project lifetime	25 years	
		Desired loss of power supply probability ($LPSP_{desired}$)	0%	[8]

		Minimum Renewable Energy fraction (*RF*)	75%	[14]
	PV	Derating factor (f_{PV})	0.9	[15]
		Temperature coefficient [%/°C]	-0.3	[16]
		Temperature at standard test condition [°C]	25	[17]
		Nominal operating cell temperature [°C]	45	[18]
		Reference irradiance [W/m2]	1000	[19]
		PV modules' life time (years)	25	[20]
		Efficiency of PV module (%)	21.82 (Industry confirmed averages for silicon solar cells)	[21]
	DG	DG Life time (hours)	24000	[8]
		DG Minimum Load Ratio (%)	25	[22]
		Slope [Liter/hr/kW output]	0.2730	[23]
		Intercept coefficient [Liter/hr/kW rated]	0.0330	[23]
	BT	BT Life time (years)	7.5 (Li-ion)	[24]
		BT minimum state of charge (SOC)	0.2	[25]
		BT maximum SOC	1	[25]

		BT initial SOC	0.5	[26]
		Battery throughput in kWh	8000	
		BT Hourly self-discharge rate	0	
		Storage's maximum charge rate [A/Ah]	1	
		Storage capacity ratio [unit less]	0.403	
		Storage rate constant [h-1]	0.827	
		Storage's maximum charge current [A]	16.7	
		Storage's nominal voltage [V]	12	
		Round trip efficiency	0.8	
	Inverter	Inverter's Life time (years)	25	[27]
		Inverter's Efficiency (%)	96	[28]

2.1 Optimization inputs

- `self.MaxIt=200`: This parameter sets the maximum number of iterations or generations the PSO algorithm will run before terminating. The algorithm will stop once it reaches this limit.
- `self.nPop = 50`: This parameter determines the population size or swarm size. It specifies the number of particles in the swarm that will be used to explore the search space for an optimal solution.
- `self.w = 1`: This is the inertia weight, a coefficient that controls the balance between the particle's previous velocity and its cognitive and social components in updating its position. A higher value for 'w' means a greater emphasis on the particle's previous velocity.
- `self.wdamp = 0.99`: Inertia weight damping ratio. Over iterations, 'w' is typically reduced to decrease the impact of the previous velocity on particle movement. This parameter specifies the rate at which the inertia weight is reduced.

- `self.c1 = 2`: Personal learning coefficient, also known as cognitive coefficient. It controls the impact of a particle's best-known solution (individual experience) on its movement.
- `self.c2 = 2`: Global learning coefficient, also known as social coefficient. It controls the impact of the best-known solution within the entire swarm (collective experience) on a particle's movement.
- `self.Run_Time = 1`: This parameter sets the total number of runs in the simulation. In some cases, you might want to run the PSO algorithm multiple times and average the results to ensure robustness in finding the optimal solution.

2.2 Lifetime and time definition

- `self.n = 25`: This parameter represents the lifetime of the energy system in the simulations, specified in years.
- `self.year = 2023`: This parameter specifies the desired year within the simulation.

2.3 Defining the electrical load

`load_type` is a variable that determines how you want to input the electrical load data. Depending on its value, different methods are used to define the load.

- If `load_type` is set to 1, the electrical load is loaded from a CSV file located at 'content/Eload.csv'. The data is read from the CSV file and stored in the `self.Eload` array.
- If `load_type` is set to 2, the electrical load is defined as monthly hourly averages. The `self.Monthly_haverage_load` array contains the hourly averages for each month, and the `dataextender` function is used to extend this data into hourly values for the entire year.
- If `load_type` is set to 3, the electrical load is defined as monthly daily averages. The `self.Monthly_daverage_load` array contains the daily averages for each month, and the code converts these to hourly averages by dividing by 24. The `dataextender` function is then used to create hourly data for the entire year.
- If `load_type` is set to 4, the electrical load is defined as monthly total load. The `self.Monthly_total_load` array contains the total load for each month, and the code calculates monthly hourly averages based on the total load and the number of days in each month. The `dataextender` function is used to extend this data into hourly values for the entire year.
- If `load_type` is set to 5, the electrical load is based on a generic load profile defined by the variable `user_defined_load`. The `generic_load` function is used to generate hourly load values based on this generic profile.
- If `load_type` is set to 6, the electrical load is defined as an annual hourly average, and all 8760 hours of the year are set to this average value.
- If `load_type` is set to 7, the electrical load is defined as an annual daily average, and the code calculates the annual hourly average by dividing the daily average by 24. All 8760 hours of the year are set to this average value.
- If `load_type` is set to 8, the electrical load is defined as an annual total load, and the code calculates the annual hourly average based on the total load and the number of days in

each month. The `generic_load` function is used to generate hourly load values based on this annual total load.

- If `load_type` is set to 9, a default generic load is used with a peak month definition of 'July or January'.

2.4 Electrical load for previous year

It is defined similar to the electrical load discussed above. **The electrical load for previous year is only needed for the situations we are going to calculate the grid costs and the monthly service charge scheme is tired rate structure.** ***In other situations, users do not need to deal with this parameter.***

2.5 Irradiance definition

- `weather_url`: This variable stores the URL or path to a weather data file in CSV format. The file is named 'METEO.csv' and likely contains weather-related data needed for simulating solar energy generation, such as solar irradiance, temperature, and other meteorological parameters. The specific content and format of the file depend on the simulation's requirements.
- `azimuth`: This variable specifies the azimuth angle in degrees, which represents the orientation of the photovoltaic (PV) modules. In this case, the azimuth is set to 180 degrees, which typically means that the PV modules are facing south.
- `tilt`: The `tilt` variable represents the tilt angle of the PV modules in degrees. A tilt angle determines the inclination of the PV panels from the horizontal plane. In this case, the tilt angle is set to 34 degrees.
- `soiling`: This variable stores the soiling loss percentage. Soiling losses refer to the reduction in energy generation due to dirt, dust, or other contaminants that accumulate on the PV modules over time.
- `G_type` is a variable that determines how you want to input solar irradiance data. Depending on its value, different methods are used to define the irradiance data.

    - If `G_type` is set to 1, SAMA uses a built-in plane of array (POA) irradiance calculator based on the weather data stored in the CSV file specified by `weather_url`. The `tilt` and `azimuth` angles of the PV modules, as well as a soiling loss percentage, are used as inputs for the simulation. The result is stored in `temp_result`, and the POA irradiance values are extracted from it and stored in the `self.G` array.
    - If `G_type` is set to 2, the solar irradiance data is loaded from a CSV file located at 'content/Irradiance.csv'. The data is read from the CSV file and stored in the `self.G` array. **Please note that if you use this option, soiling losses will not be induced by SAMA itself.**

2.6 Temperature definition

`T_type` is a variable that determines how you want to input temperature data for your simulation. Depending on its value, different methods are used to define the temperature data.

- If `T_type` is set to 1, the code imports the `runSimulation` function from the `sam_monofacial_poa` module. This function is used to simulate temperature data based on the provided weather data, tilt, azimuth, and soiling parameters. The temperature data is extracted and stored in the `self.T` array.
- If `T_type` is set to 2, the temperature data is loaded from a CSV file located at 'content/Temperature.csv'. The data is read from the CSV file and stored in the `self.T` array.
- If `T_type` is set to 3, the temperature data is defined as monthly hourly averages. The `self.Monthly_average_temperature` array contains the hourly averages for temperature for each month. The `dataextender` function is used to extend this data into hourly values for the entire year.
- If `T_type` is set to 4, the temperature data is defined as an annual average temperature. The `self.Annual_average_temperature` variable is set to desired annual average, and all 8760 hours of the year are set to this average temperature.

2.7 Wind speed definition

`WS_type` is a variable that determines how you want to input wind speed data for your simulation. Depending on its value, different methods are used to define the wind speed data.

- If `WS_type` is set to 1, the code imports the `runSimulation` function from the `sam_monofacial_poa` module. This function is used to simulate wind speed data based on the provided weather data, tilt, azimuth, and soiling parameters. The wind speed data is extracted and stored in the `self.Vw` array.
- If `WS_type` is set to 2, the wind speed data is loaded from a CSV file located at 'content/WSPEED.csv'. The data is read from the CSV file and stored in the `self.Vw` array.
- If `WS_type` is set to 3, the wind speed data is defined as monthly hourly averages. The `self.Monthly_average_windspeed` array contains the hourly averages for wind speed for each month. The `dataextender` function is used to extend this data into hourly values for the entire year.
- If`WS_type` is set to 4, the wind speed data is defined as an annual average wind speed. The `self.Annual_average_windspeed` variable is set to desired annual wind speed, and all 8760 hours of the year are set to this average wind speed.

2.8 Technical inputs

2.8.1 Type of systems included in simulations

- `self.PV`: This indicates that a photovoltaic (PV) system is included in the simulation (with a value of 1) or not (with a value of 0).
- `self.WT`:This indicates that a a wind turbine (WT) system is included in the simulation (with a value of 1) or not (with a value of 0).
- `self.DG`: This indicates that a diesel generator (DG) system is included in the simulation (with a value of 1) or not (with a value of 0).
- `self.Bat`: This indicates that a battery system in the simulation (with a value of 1) or not (with a value of 0).
- `self.Grid = 1`: This indicates if grid interconnection is included in the simulation, indicated by a value of 1. If you want to simulate an off-grid system without a grid connection, you would set this to 0.

- `self.NEM = 1`: This parameter is related to net metering. If set to 1, it means that compensation in the net metering scheme is provided as credits, not as monetary compensation. In this case, yearly credits will be reconciled after 12 months.

2.8.2 Constraints

- `self.LPSP_max_rate`: This parameter represents the maximum acceptable loss of power supply probability (LPSP) in percentage form.
- `self.RE_min_rate`: This parameter represents the minimum required renewable energy (RE) capacity as a percentage.

2.8.3 Multi-objective optimization

If `self.EM = 0`the objective for optimization is only NPC while if `self.EM = 1` the objectives for optimization are NPC and levelized emission (LE).

2.8.4 Rated capacity (DO NOT CHANGE)

2.8.5 PV technical parameters

- `self.fpv = 0.9`: This parameter represents the derating factor for the PV module, expressed as a percentage (90%). It accounts for efficiency losses and performance degradation in the PV module over time.
- `self.Tcof = 0`: The temperature coefficient for the PV module, expressed as a percentage per degree Celsius (%/°C). It quantifies how the PV module's performance is affected by changes in temperature.
- `self.Tref = 25`: The reference temperature at standard test conditions for the PV module, typically 25°C. This is used to normalize the module's performance data.
- `self.Tc_noct = 45`: The nominal operating cell temperature for the PV module. It represents the temperature of the PV cells during operation under specified conditions.
- `self.Ta_noct = 20`: The ambient temperature used for determining the nominal operating cell temperature. It is typically lower than the cell temperature due to the module's heat dissipation.
- `self.G_noct = 800`: The solar irradiance at the nominal operating cell temperature. It represents the solar radiation level used to calculate the NOCT.
- `self.gama = 0.9`: A parameter related to the conversion efficiency of the PV module.
- `self.n_PV = 0.2182`: The efficiency of the PV module. This value likely represents the efficiency of converting incident solar energy into electrical energy.
- `self.Gref = 1000`: The reference solar irradiance level, typically 1000 watts per square meter (W/m^2), used for normalizing PV module performance data.
- `self.L_PV = 25`: The lifetime of the PV module in years. This parameter defines the expected operational lifespan of the PV module in your simulation.

2.8.6 WT technical parameters

- `self.h_hub = 17`: This parameter represents the hub height of the wind turbine in meters. It specifies the height at which the wind turbine is mounted, and it is an important factor affecting wind energy capture.
- `self.h0 = 43.6`: The anemometer height in meters. Anemometer height is the height at which wind speed measurements are taken and is typically used to calculate wind shear.
- `self.nw = 1`: The electrical efficiency of the wind turbine, expressed as a decimal. It indicates the fraction of the wind's kinetic energy that is converted into electrical energy.

- `self.v_cut_out = 25`: The cut-out speed in meters per second (m/s). When the wind speed exceeds this value, the wind turbine is typically shut down or "cut out" to prevent damage.
- `self.v_cut_in = 2.5`: The cut-in speed in meters per second (m/s). It is the wind speed at which the wind turbine starts operating and generating electricity.
- `self.v_rated = 9.5`: The rated speed of the wind turbine in meters per second (m/s). This is the wind speed at which the wind turbine generates its maximum rated power.
- `self.alfa_wind_turbine = 0.14`: The coefficient of friction. This parameter is used to model the effects of friction on the wind turbine's performance. The value may vary depending on wind conditions, with lower values for extreme wind conditions and higher values for normal wind conditions.
- `self.L_WT = 20`: The lifetime of the wind turbine in years. This parameter defines the expected operational lifespan of the wind turbine in your simulation.

2.8.7 DG technical parameters

- `self.LR_DG = 0.25`: This parameter represents the minimum load ratio for the DG system, expressed as a percentage (%). It specifies the minimum load that the DG can operate at efficiently.
- Diesel Generator Fuel Curve:

    - `self.a = 0.2730`: The coefficient 'a' in liters per hour per kilowatt (L/hr/kW) of DG output. It is used to model the DG's fuel consumption rate as a function of its output power.
    - `self.b = 0.0330`: The coefficient 'b' in liters per hour per kilowatt (L/hr/kW) of the DG's rated power. It is used in the fuel consumption model.

- `self.TL_DG = 24000`: The lifetime of the diesel generator in hours. This parameter defines the expected operational lifespan of the DG in your simulation.
- Emissions produced in gr by DG for liter of fuel consumed

    - `self.CO2`: The emission level of carbon dioxide (CO2) in grams per liter (g/L) of fuel. CO2 is a greenhouse gas and a major contributor to global warming.
    - `self.CO`: The emission level of carbon monoxide (CO) in grams per liter (g/L) of fuel. Carbon monoxide is a harmful air pollutant that can have adverse effects on air quality and human health.
    - `self.NOx`: The emission level of nitrogen oxides (NOx) in grams per liter (g/L) of fuel. NOx includes nitrogen dioxide (NO2) and nitric oxide (NO), which are harmful air pollutants and contribute to smog and acid rain.
    - `self.SO2`: The emission level of sulfur dioxide (SO2) in grams per liter (g/L) of fuel. SO2 is a harmful air pollutant that can lead to respiratory problems and contribute to acid rain.

2.8.8 Battery technical parameters

- `self.SOC_min = 0.2`: The minimum state of charge (SOC) of the battery. SOC represents the fraction of the battery's capacity that is currently used, and this parameter sets the minimum allowed SOC.
- `self.SOC_max = 1`: The maximum SOC of the battery, representing the fully charged state. It is typically set to 1 for full capacity.

- `self.SOC_initial = 0.5`: The initial SOC of the battery when the simulation starts.
- `self.Q_lifetime = 8000`: The lifetime capacity of the battery, expressed in kilowatt-hours (kWh). This value represents the total energy that the battery is capable of storing over its lifetime.
- `self.self_discharge_rate = 0`: The hourly self-discharge rate of the battery, which is a measure of how much energy is lost over time due to self-discharge. A rate of 0 indicates no self-discharge.
- `self.alfa_battery = 1`: The storage's maximum charge rate, given as a ratio of charge current to the battery's capacity (A/Ah). This parameter is related to the battery's charge and discharge characteristics.
- `self.c = 0.403`: The storage capacity ratio, which is a unitless parameter related to the battery's capacity and performance.
- `self.k = 0.827`: The storage rate constant, given in units of per hour (h^{-1}). This parameter influences the rate at which the battery can charge or discharge.
- `self.Imax = 16.7`: The battery's maximum charge current, expressed in amperes (A).
- `self.Vnom = 12`: The battery's nominal voltage, specified in volts (V).
- `self.ef_bat = 0.8`: The round-trip efficiency of the battery. This parameter represents the efficiency of charging and discharging the battery.
- `self.L_B = 7.5`: The lifetime of the battery in years. This parameter defines the expected operational lifespan of the battery in your simulation.

2.8.9 Inverter

- `self.n_I`: This parameter represents the efficiency of the inverter. It is expressed as a decimal and indicates the fraction of electrical power that is converted from direct current (DC) to alternating current (AC) by the inverter.
- `self.L_I`: The lifetime of the inverter in years. This parameter defines the expected operational lifespan of the inverter in your simulation.
- `self.DC_AC_ratio`: The maximum acceptable DC to AC ratio. This parameter specifies the maximum ratio of DC power (input) to AC power (output) that the inverter can handle efficiently.

2.8.10 Charger

The parameter `self.L_CH` is related to the charge controller used in your simulation and represents the lifetime of the charger in years.

2.9 Economic inputs

- `self.n_ir_rate`: The nominal discount rate, expressed as a percentage. It represents the rate at which future cash flows are discounted to determine their present value.
- `self.e_ir_rate`: The expected inflation rate, expressed as a percentage. It accounts for the expected rate of price inflation over time..
- `self.Budget`: The budget or limit on the total capital cost for the project, expressed in dollars. This parameter sets a constraint on the total capital expenditure.
- `self.Tax_rate`: The equipment sales tax rate, expressed as a percentage. It represents the percentage of tax applied to the purchase of equipment.
- `self.RE_incentives_rate`: The federal tax credit rate for renewable energy incentives, expressed as a percentage. This parameter represents the percentage of federal tax credit that can be applied to the project.

2.9.1 Top down pricing inputs

- `self.Pricing_method`: This parameter is used to determine the pricing method. If it is set to "1", it refers to the **top-down pricing** method and "2" refers to **bottom up pricing** method. In the **top-down pricing** method, the PV system costs are broke down based on NREL PV cost benchmarks. In **bottom up pricing** method, users need to define each equipment cost in detail (Capital, replacement and maintenance).

For top-down pricing method:

- `Total_PV_price = 2950`: The total price for PV system (PV+inverter+engineering costs) in $ per kW. This is the initial cost of the PV system.
- Rather than PV and inverter, users need to define costs in $ per kW for other system components and $ per kWh for battery, such as wind turbines (WT), diesel generators (DG), batteries (B), and chargers (CH), including their capital costs, replacement costs, and operation and maintenance (O&M) costs. These costs are based on the capital costs and replacement costs in dollars.
- Some components, like the diesel generator (DG) fuel cost, also consider yearly escalation or reduction rates in fuel cost.

top-down pricing allows you to model the initial and ongoing costs of the various components of your energy system. The top-down pricing method starts with the total cost and allocates it to individual components based on predefined relationships and cost factors.

2.9.2 Bottom up pricing inputs

This approach specifies the costs associated with individual components of the energy system. Here's a breakdown of the pricing information for each component:

- Engineering Costs (per/kW):
  - `self.Installation_cost = 160`: The cost of installation per kilowatt (kW) of installed capacity.
  - `self.Overhead = 260`: Overhead costs per kW.
  - `self.Sales_and_marketing = 400`: Sales and marketing costs per kW.
  - `self.Permiting_and_Inspection = 210`: Permitting and inspection costs per kW.
  - `self.Electrical_BoS = 370`: Electrical balance of system (BoS) costs per kW.
  - `self.Structural_BoS = 160`: Structural BoS costs per kW.
  - `self.Supply_Chain_costs = 0`: Supply chain costs per kW.
  - `self.Profit_costs = 340`: Profit costs per kW.
  - `self.Sales_tax = 80`: Sales tax per kW.
  - `self.Engineering_Costs`: The total engineering costs per kW, calculated as the sum of all the individual cost components.
- PV (Photovoltaic) System:

  - `self.C_PV = 2510`: The capital cost of the PV system per kW.
  - `self.R_PV = 2510`: The replacement cost of PV modules per kW.
  - `self.MO_PV = 28.12`: The annual O&M cost per kW.
- Inverter:
  - `self.C_I = 440`: The capital cost of the inverter per kW.
  - `self.R_I = 440`: The replacement cost of the inverter per kW.
  - `self.MO_I = 3`: The annual O&M cost per kW.
- Wind Turbine (WT) System:
  - `self.C_WT = 1200`: The capital cost of the wind turbine system per kW.
  - `self.R_WT = 1200`: The replacement cost of wind turbines per kW.
  - `self.MO_WT = 40`: The annual O&M cost per kW.
- Diesel Generator (DG) System:
  - `self.C_DG = 240.45`: The capital cost of the diesel generator system per kW.
  - `self.R_DG = 240.45`: The replacement cost of the diesel generator per kW.
  - `self.MO_DG = 0.064`: The annual O&M cost per operating hour.
  - `self.C_fuel = 1.39`: The fuel cost per liter for the DG system.
  - `self.C_fuel_adj_rate = 2`: The yearly escalation or reduction rate of DG fuel costs.
  - `self.C_fuel_adj = self.C_fuel_adj_rate / 100`: The rate converted to a decimal form.
- Battery System:
  - `self.C_B = 458.06`: The capital cost of the battery system per kWh.
  - `self.R_B = 458.06`: The replacement cost of the battery per kWh.
  - `self.MO_B = 10`: The annual maintenance cost per kWh.
- Charger:
  - `self.C_CH = 149.99 * (1 + self.r_Sales_tax)`: The capital cost of the charger. The sales tax is applied to the cost.
  - `self.R_CH = 149.99 * (1 + self.r_Sales_tax)`: The replacement cost of the charger. The sales tax is applied to the cost.
  - `self.MO_CH = 0 * (1 + self.r_Sales_tax)`: The annual O&M cost for the charger. The sales tax is applied to the cost.

2.9.3 Grid & Utility structures

For the U.S., the main electric utility prices structures are predesigned in SAMA.

2.9.3.1 Flat rate

Some electric utility companies utilize a flat rate electric utility structure to bill customers at a fixed rate for their electricity usage, irrespective of the time of day or the quantity of electricity consumed. With the flat rate structure, customers are billed a fixed rate for each unit of electricity they consume (typically measured in kilowatt-hours, kWh) throughout the billing period, regardless of the varying costs or demands for electricity during different time periods. The flat rate concept is modeled SAMA in there different structure so that users can choose whatever works best for them. The first structure is considering a fixed price for the whole year, while the second and third structures consider flat rates for each season (summer and winter) and each month, respectively.

2.9.3.2 Tiered rate

The tier-based electricity structure is a billing method that categorizes electricity consumption into different tiers or levels, each with its own associated rate. The consumption levels are typically determined by the amount of electricity used during a billing period. As customers consume more electricity, they move into higher tiers with higher rates, while lower tiers offer lower rates for lower consumption levels. In SAMA, tired base structure is designed into three different formats and users can choose whichever works best for them. First option model the tier based structure for the full year considering three different tiers. The other one considers three tiers for each season (summer and winter). A comprehensive tiered base structure is also defined in SAMA which considers three tiers for each month. As an example, Fig.1, illustrates the ToU structure for Tucson, Arizona [29].

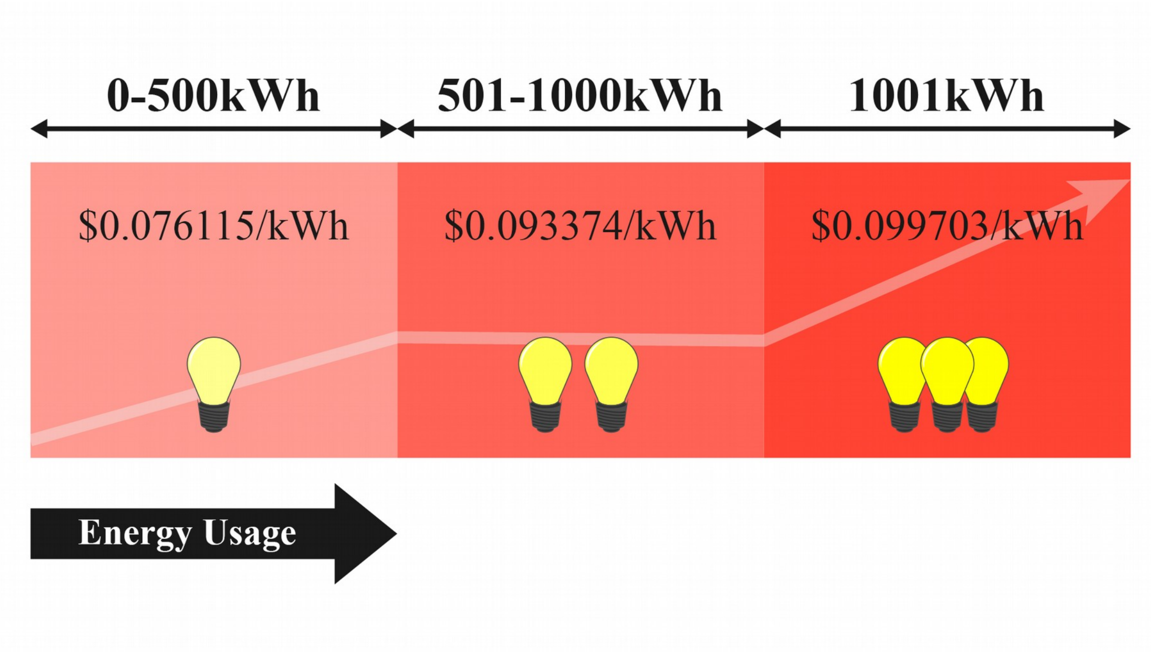

Fig.1. Tiered base utility structure for Tucson, Arizona

2.9.3.3 Time of Use (ToU)

The time-of-use pricing model is an electricity billing approach that adjusts rates according to the specific time of day, motivating customers to shift their energy consumption to periods with lower demands using rates. By encouraging reduced electricity usage during peak hours, customers can align their consumption patterns with the varying costs associated with generating electricity throughout the day [30], [31]. In SAMA, ToU is designed for both summer and winter seasons. For both seasons, separate on-peak, mid-peak and off-peak hours and prices can be defined. Also, users can define from which month to which month is summer or winter. As an example, Fig.2, illustrates the ToU structure for Sacramento, California [32].

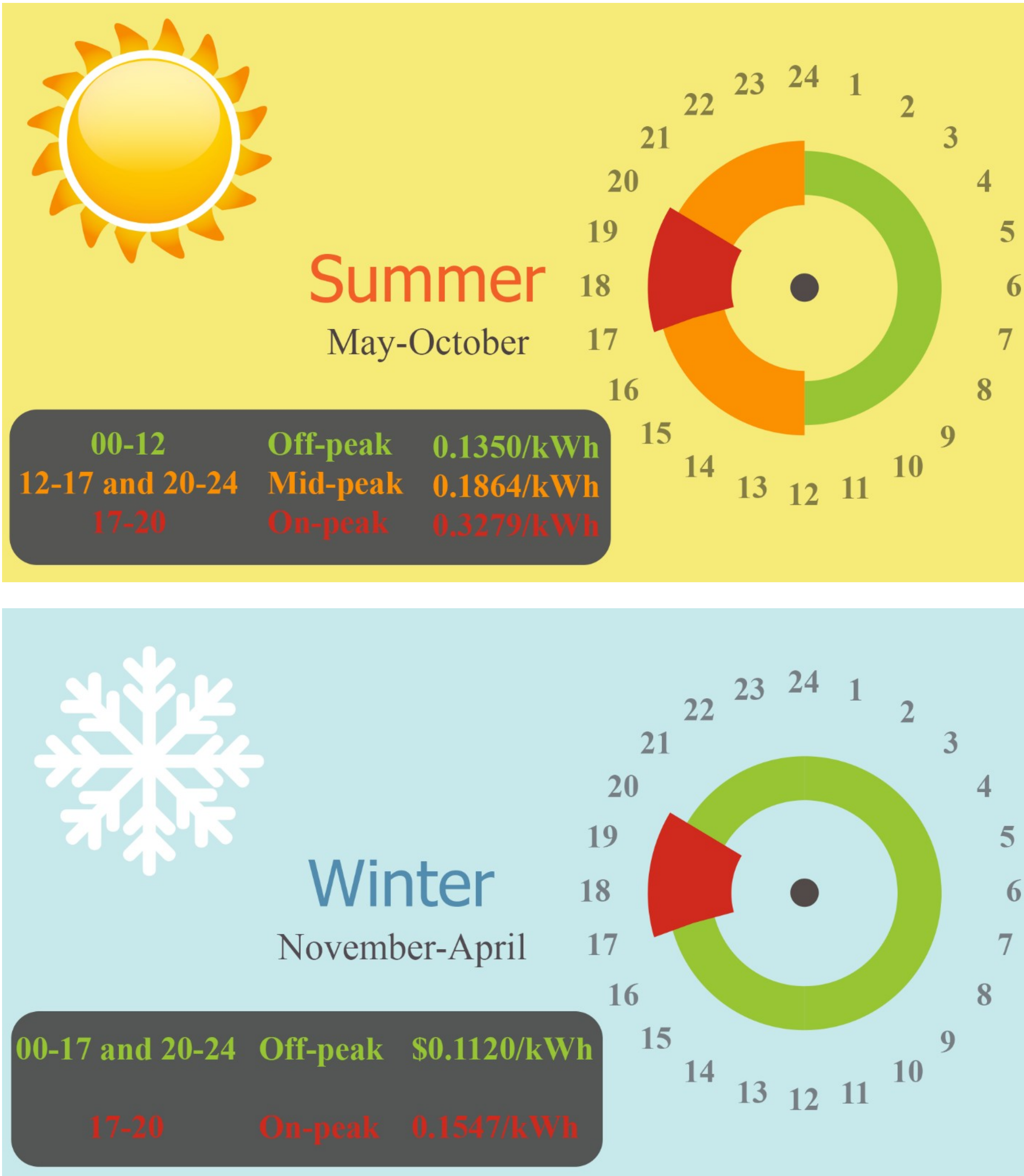

Fig.2. ToU utility structure for summer and winter, Sacramento, California

2.9.3.4 Defining prices for electric utilities

- `self.rateStructure`: This parameter specifies the hourly rate structure for electricity prices. The values below for this parameter show the corresponding rate structure. Users can choose whichever fits them best.

```
1 = flat rate
2 = seasonal rate
3 = monthly rate
4 = tiered rate
5 = seasonal tiered rate
6 = monthly tiered rate
7 = time of use rate
```

- `self.Annual_expenses`: This parameter represents any annual expenses in dollars associated with the grid.
- `self.Grid_sale_tax_rate`: This parameter represents the sales tax percentage applied to grid electricity prices.
- `self.Grid_Tax_amount`: This parameter represents a grid tax applied in kilowatt-hours (kWh).
- `self.Grid_escalation_rate`: This parameter defines the yearly escalation rate for grid electricity prices, expressed as a percentage.
- `self.Grid_credit`: This parameter represents any credits offered by the grid to users in dollars.
- `self.NEM_fee`: This parameter represents any one-time setup fee for net metering.

2.9.3.4.1 Monthly service charge (buying prices)

`self.Monthly_fixed_charge_system`: This parameter specifies the type of monthly fixed charge structure. If it is set to "1" indicating a flat monthly rate over the year and if it is "2", indicating a tiered structure for monthly charges. The `self.SC_flat`is the monthly flat charge in structure 1.

Structure 2 includes tier-specific service charge values and limits for each tier:

`self.SC_1 = 2.30`: The service charge for tier 1 in $.

`self.Limit_SC_1 = 350`: The limit for tier 1 in kWh.

`self.SC_2 = 7.9`: The service charge for tier 2 in $.

`self.Limit_SC_2 = 1050`: The limit for tier 2 in kWh.

`self.SC_3 = 22.70`: The service charge for tier 3 in $.

`self.Limit_SC_3 = 1501`: The limit for tier 3 in kWh.

`self.SC_4 = 22.70`: The service charge for tier 4 in $.

2.9.3.4.2 Utility hourly charges (buying prices)

How to define hourly charges for grid:

1. **Set Rate Structure:**
   - Determine the rate structure you want to simulate. The rate structure is specified by the `self.rateStructure` variable.
2. **Configure Rate Parameters:**
   - Depending on the chosen rate structure, configure the rate parameters accordingly:
     - For flat rate, set the `self.flatPrice`.
     - For seasonal rate, specify seasonal prices in `self.seasonalPrices` and define the season in `self.season`.
     - For monthly rate, provide monthly prices in `self.monthlyPrices`.
     - For tiered rate, set tiered prices in `self.tieredPrices` and tier maximums in `self.tierMax`.
     - For seasonal tiered rate, provide seasonal tiered prices and maximums in `self.seasonalTieredPrices` and `self.seasonalTierMax`.
     - For monthly tiered rate, configure monthly tiered prices and maximums in `self.monthlyTieredPrices` and `self.monthlyTierLimits`.
     - For time-of-use rate, specify on-peak, mid-peak, and off-peak prices, special hours for holidays, and the season in `self.onPrice`, `self.midPrice`, `self.offPrice`, `self.holidays`, `self.season`, and the time-of-use hours in `self.onHours` and `self.midHours`.

2.9.3.4.3 Sell back prices to the grid

How to define hourly sell back prices to the grid:

1. **Set Sell Structure:**
   - Determine the structure for selling electricity to the grid by setting the `self.sellStructure` variable. You can choose from three options:
     - `1`: Flat rate for selling electricity back to the grid.
     - `2`: Monthly rate for selling electricity back to the grid.
     - `3`: Selling electricity back to the grid at the same rate you buy it.
2. **Configure Sell Rates:**
   - Depending on the chosen sell structure, configure the sell rates accordingly:
     - For flat rate (sellStructure = 1), set the desired flat sell rate in the `self.Csell` variable.
     - For monthly rate (sellStructure = 2), provide an array of monthly sell prices in `self.monthlysellprices`. The array should contain 12 values, one for each month.
     - For selling at the same rate as you buy (sellStructure = 3), you can set `self.Csell` to `self.Cbuy`. This means you will sell electricity back to the grid at the same rate you buy it.

2.9.3.4.4 Grid emission information

- `self.E_CO2`: The emission level of carbon dioxide (CO2) in kg per kWh of electricity bought from grid.
- `self.E_NOx`: The emission level of nitrogen oxides (NOx) in kg per kWh of electricity bought from grid.
- `self.E_SO2`: The emission level of sulfur dioxide (SO2) in kg per kWh of electricity bought from grid.

2.9.3.4.5 Constraints for buying/selling from/to grid

These lines of code set constraints for buying and selling electricity from/to the grid:

- `self.Pbuy_max`: This represents the maximum amount of electricity that can be bought from the grid in each hour in kW (**Maximum buying capacity**).
- `self.Psell_max`: This represents the maximum amount of electricity that can be sold to the grid in each hour in kW (**Maximum selling capacity**).

3 How to use SAMA

Step.1

Obtain the input data for simulations! To run SAMA, the user needs to define some data such as electrical load, temperature, irradiance, wind speed (if wind turbine is included in simulation), and costs. Hourly electrical load data for U.S different cities in a year (8760 values) can be downloaded from NREL library. Then in this file, extract the second column values from second row to the last value (8760 values) and replace them with first column of **Eload.csv** inside the **content folder**. Meteorological data (temperature, irradiance, wind speed) can be downloaded for any location in the world from NSRDB and be placed inside the **content folder** with **METEO.csv** name. Please note that when you download these data from NSRDB, the time interval should be 60 mins, and check to download DHI, DNI, Fill Flag, GHI, Ozone, Relative Humidity, Solar Zenith Angle, Surface Albedo, Pressure, Precipitable Water, Wind Direction, and Wind Speed (**all meteorological the data**). When defined electrical load and meteorological data or you decide how you want to define them, you need to define other inputs as discussed below completely (**under Input_Data.py**).

Step.2

Open the **pso.py** file in your preferred Python compiler and run it. For example, if user uses PyCharm environment, they just need to open **pso.py** in their PyCharm and run it! To run the code without error, user needs to make sure required Python packages (***NumPy, Numba, time, pandas, math, matplotlib and seaborn***) are installed prior to the run.

Enjoy!

4 SAMA framework

The SAMA framework is discussed comprehensively in this section including concepts and calculations. The SAMA framework relies on a comprehensive energy management strategy (EMS) to achieve its goals. The EMS is a structured and holistic approach that encompasses various elements and techniques to effectively manage and distribute energy throughout the entire system. The hybrid energy system in SAMA includes four major parts: 1) PV modules, 2) diesel generator (DG), 3) inverter, and 4) batteries.

4.9 PV modeling

Power output of PV modules (P_{PV} [kW]) and corresponding PV energy (E_{PV} [kW.h]) with simulation time-step of t, is the function of module's temperature (T_{Module} [°C]) as well as plane of array irradiance (POA [W/m^2]), which can be calculated from following formula [33]–[35]:

$$P_{PV}[kW]=N_{PV} f_{PV} \times P_{PV}^{STC}\left(\frac{POA}{POA_{STC}}\right)\left[1+\delta_{PV}\left(T_{Module}-T_{\Re f}\right)\right]; E_{PV}=P_{PV}\, t \qquad \text{[kW] (3)}$$

Where N_{PV} stands for optimum capacity of PV system, f_{PV} is PV derating factor, P_{PV}^{STC} [kW] is rated capacity of PV array at STC conditions (irradiance of 1000 W/m^2 and temperature of 25 °C (T_{Ref})), POA_{STC} [W/m^2] is POA at STC, δ_{PV} denotes the PV temperature coefficients at STC (−3.7 × 10^{-3} (1/°C)) [36], and T_{Module} is calculated form Eq.4 [37]:

$$T_{Module}[°C]=T_{Amb}+\left(\frac{T_{noct}-20}{800}\right)\times POA \qquad (4)$$

In which T_{noct} [°C] is nominal operating module temperature, depending on specification of PV module determined by manufacturer, and T_{Amb} [°C] is the ambient temperature.

4.10 Battery modeling

A battery bank used to overcome the uncertainty in electrical supply based solely on solar resources. The Kinetic Battery Model (KiBaM) [38] is utilized in this study to model the energy storage system. This model, firstly developed for lead-acid batteries is used for quasi-steady state time-series simulation of hybrid power systems. This model is effective for lithium-ion and other types of batteries as well [39]–[42]. Manwell and McGowan [38] compared KiBaM results analytically with Battery Energy Storage Test (BEST) model [43]. They reported that KiBaM works better than BEST. It is worth mentioning that KiBaM is comprehensively evaluated, utilized and validated in the literature [44]–[48]. For example, it is the battery model used for Homer Pro software.

The battery storage concept of KiBaM combines phenomenological and physical effects. It presumes that a battery has two reservoirs. The available energy is held by one, while the bound energy is held by the other. Energy delivery from/to the bound energy reservoir is transferred when the available energy reservoir is depleted or charged. Based on the KiBaM [38], the maximum amount of power that can be charged through battery in kW ($P_{BT,ch}^{max,KiBaM}$¿, can be calculated from Eq.5, in which Q_1, Q_{max} and Q are available energy at the first of time-step [kWh], total capacity of storage bank [kWh], and total energy reserved at the storage at the first of time-step [kWh], respectively. c and k are storage capacity ratio and the storage rate constant, respectively and t is the simulation time-step.

$$P_{BT,ch}^{max,KiBaM} = \frac{kc\,Q_{Max} + kQ_1 e^{-kt} + Qkc\left(1-e^{-kt}\right)}{1-e^{-kt} + c\left(k\,\Delta t - 1 + e^{-kt}\right)};\ E_{BT,ch}^{max,KiBaM} = P_{BT,ch}^{max,KiBaM}\,t \qquad \text{[kW]} \quad (5)$$

$E_{BT,ch}^{max,KiBaM}$ is the maximum chargeable energy in battery bank in kWh. HOMER [49] considers two more limits for maximum charge power based on the maximum charge rate (α ¿ [A/Ah] and current (I_{max}¿ which are defined below:

$$P_{BT,ch}^{max,mcr} = \frac{(1-e^{-\alpha t})(Q_{max}-Q)}{t};\ E_{BT,ch}^{max,mcr} = P_{BT,ch}^{max,mcr} t \qquad \text{[kW] (6)}$$

$$P_{BT,ch}^{max,mcc} = \frac{N_{BT} I_{max} V_{nom}}{1000};\ E_{BT,ch}^{max,mcc} = P_{BT,ch}^{max,mcc} t \qquad \text{[kW] (7)}$$

In equations above, $P_{BT,ch}^{max,mcr}$ is maximum battery bank charge power [kW] based on α, $E_{BT,ch}^{max,mcr}$ is the maximum battery bank charge energy [kWh] based on α, $P_{BT,ch}^{max,mcc}$ is the maximum battery bank charge power [kW] based on charging current [A] (I_{max}¿, N_{BT} is the number of batteries in the storage, V_{nom} is the storage nominal voltage [V], and $E_{BT,ch}^{max,mcc}$ is the maximum bank charge energy [kWh] based on (I_{max}¿. The reason that Homer Pro considers two more limits for charging power through battery bank is that battery bank should not be charged with higher charging rate and current compared to allowable charging rate and current (limit formula defined in Eq.6 and Eq.7, respectively). These limits were used in SAMA as well. Finally, the maximum power and energy which can be charged through battery storage can be calculated from follow:

$$P_{BT,ch}^{max} = \frac{Min\left(P_{BT,ch}^{max,KiBaM}\ P_{BT,ch}^{max,mcr}, P_{BT,ch}^{max,mcc}\right)}{\eta_{BT}};E_{BT,ch}^{max} = P_{BT,ch}^{max} t \qquad \text{[kW] (8)}$$

Where η_{BT} is the storage round-trip efficiency. The maximum power and energy based on KiBaM which can be discharged through battery storage ($P_{BT,dch}^{max,KiBaM}$) can be calculated from Eq.9.

$$P_{BT,dch}^{max,KiBaM} = P_{BT,dch}^{max} = \frac{k Q_1 e^{-t} + Qkc\left(1-e^{-kt}\right)}{1-e^{-kt}+c\left(k\Delta t - 1 + e^{-kt}\right)};E_{BT,dch}^{max} = P_{BT,dch}^{max} t \qquad \text{[kW] (9)}$$

The battery marginal cost of energy, a.k.a battery wear cost [50]–[52]($\cos t_{BT}^{Wear}$) can be calculated from Eq.10:

$$\cos t_{BT}^{Wear} = \frac{R_{BT} \times N_{BT}^{total}}{N_{bat} \times Q_{lifetime} \times \sqrt{\eta_{BT}}} \qquad (10)$$

where, R_{BT} is replacement cost of battery per kWh, N_{BT}^{total} is the total capacity of battery storage, N_{bat} is the number of batteries in storage bank.

4.11 Diesel generator (DG) modeling

DG has an backup role in the EMS and is modeled based on Eq.11, in which b is, $P_{DG}^{Nominal}$ is the total rated power of all DGs in the system [52]–[54], $Cost_{fuel}$ is the diesel fuel cost per liter, R_{DG} denotes replacement cost of DG, TL_{DG} stands for total life time of DG in hours, MO_{DG} is maintenance and operation costs of DG ($/h) and a is.

$$\cos t_{DG} = b \times P_{DG}^{Nominal} \times \cos t_{fuel} + \frac{R_{DG} \times P_{DG}^{Nominal}}{TL_{DG}} + MO_{DG} + a \times \cos t_{fuel} \tag{11}$$

4.12 Inverter modeling

The inverter model is based on considering the efficiency of converting DC electricity to AC (η_{inv}), as described in the energy management strategy (EMS) section.

4.13 Energy management strategy (EMS)

The real-time demand for electricity of a representative household cannot be satisfied entirely by renewable sources of energy (i.e., PV) alone because people use electricity at night, during cloudy weather, etc. To maintain a balance between demand and PV generation, the battery, grid interconnection and DG can be linked with the renewable energy sources to provide load matching. To minimize the use of fuel, renewable energy sources is used to full capacity and limit the use of the grid interconnection, battery and DG. This is only possible with a suitable and well-designed EMS [8]. The primary energy source is provided by renewable energy sources (PV modules), then the stored solar energy in the battery; while the DG and grid serve as a backup (dispatchable source).

An advanced load following strategy [55], [56] is implemented in the SAMA to control flow of energy from various sources, for the purpose of charging and discharging ESS.

In the load following dispatch strategy the DG and grid is used to satisfy the load, *only if needed*. If energy produced by renewable sources (E_{RE}) is higher than demand (E_{load}), then the battery is charged based on the surplus energy (E_{AC}^{sur}) in the system and the empty capacity of battery storage (E_{BT}^{empty}). Charged energy stored in battery (E_{BT}^{ch}¿ can be calculated from Eq.12, while the battery empty capacity and surplus energy on the AC side (E_{AC}^{sur}) are calculated from Eq.13 and Eq.14, respectively. Energy stored in the battery in each time-step is $E_{BT}(t)$. E_{BT}^{max} is the maximum capacity of battery, which is multiplication of SOC_{max} and storage capacity (N_{BT}^{total}).

$$E_{BT}^{ch}(t)=min\left(E_{BT}^{empty},E_{\Re}(t)-\frac{E_{load}(t)}{\eta_{inv}}\right)\wedge E_{BT}^{ch}(t)=\min\ (E_{BT}^{ch}(t),E_{BT,ch}^{max}) \qquad \text{[kWh] (12)}$$

$$E_{BT}^{empty}=\frac{E_{BT}^{max}-E_{BT}}{\eta_{BT}} \qquad \text{[kWh] (13)}$$

$$E_{AC}^{sur}=\eta_{inv}\times(E_{\Re}(t)-E_{BT}^{ch}(t))-E_{load}(t) \qquad \text{[kWh] (14)}$$

In addition to the charging battery, the surplus energy generated by renewable resources can be sold to the Grid using Eq.15, in which E^{sell} is the amount of energy sold to the grid, $E^{sell,max}$ is the sale capacity in each hour (the maximum amount of energy that can be sold in each hour) and E_{inv}^{max} is the maximum energy capacity of inverter. E_{inv}^{max} comes from random values by PSO optimizations.

$$E^{sell}(t)=min\left(E_{AC}^{sur},E^{sell,max}\right)\wedge E^{sell}(t)=min\ (max(0,E_{inv}^{max}-E_{load})),E^{sell}(t)¿ \qquad \text{[kWh] (15)}$$

On the other hand, if renewable resources cannot meet the demand, the unsatisfied load on the AC side should is given by:

$$Ens_{AC}(t)=E_{load}(t)-min(E_{inv}^{max},\eta_{inv}\times E_{\Re}(t)) \qquad \text{[kWh] (16)}$$

In this situation, ($E_{load}>E_{\Re}$¿,six scenarios can happen so that unsatisfied load can be met by other energy sources (DG, BT and grid):

First scenario: If the price of buying electricity from grid (C_{buy}) is lower than cost of energy generation by DG ($\cos t_{DG}¿$ *and* battery wear cost ($\cos t_{BT}^{Wear}¿$ is higher than cost of energy generation by DG, it is cost effective to firstly buy electricity from the grid using Eq.17 in which $E^{buy,max}$ is the buy capacity in each hour (the maximum amount of energy that can be bought in each hour). Then DG can be used instead of the battery, hence based on the rated energy capacity of DG (E_{rated}^{DG}), Ens_{AC}, and its minimum operating capacity (E_{DG}^{min}), DG should run and operate, using Eq.18 and Eq.19. In this equation, E^{buy} is the amount of energy bought from the grid in time-step (t).

$$E^{buy}(t)=min\left(Ens_{AC}(t),E^{buy,max}\right) \quad \text{[kWh]} \quad (17)$$

$$E_{DG}(t)=min\left(Ens_{AC}(t)-E^{buy}(t),E_{DG}^{rated}\right) \quad \text{[kWh]} \quad (18)$$

$$E_{DG}(t)=E_{DG}(t)\left(E_{DG}(t)\geq LR_{DG}E_{DG}^{rated}\right)+LR_{DG}E_{DG}^{rated}\left(E_{DG}(t)<LR_{DG}E_{DG}^{rated}\right)\left(E_{DG}(t)>E_{DG}^{min}\right)$$
[kWh] (19)

In Eq.19, conditions like $\left(E_{DG}(t)\geq LR_{DG}E_{DG}^{rated}\right),\left(E_{DG}(t)<LR_{DG}E_{DG}^{rated}\right)$ or $\left(E_{DG}(t)>E_{DG}^{min}\right)$ are Boolean conditions, treating "True" as 1 and "False" as 0. In the situations where the load cannot be met by the renewable resources, grid and diesel generator, the battery is also can be discharged. The discharged energy [kWh] from battery (E_{BT}^{dch}) can be calculated from Eq.20:

$$E_{BT}^{dch}(t)=\min\left(E_{BT}^{empty},Ens_{DC}(t)\right)¿E_{BT}^{dch}(t)=\min\left(E_{BT}^{dch}(t),E_{BT,dch}^{max}\right) \quad \text{[kWh]} \quad (20)$$

where, E_{BT}^{empty} can be calculated from Eq.21, in which $E_{BT,min}$ is the minimum energy in battery (multiplication of SOC_{min} and storage capacity (N_{BT}^{total})). $Ens_{DC}(t)$ can be calculated from Eq.22.

$$E_{BT}^{empty}=\left(E¿¿BT(t)-E_{BT,min}\right)\sqrt{\eta_{BT}}¿ \quad \text{[kWh]} \quad (21)$$

$$Ens_{AC}(t)=E_{load}(t)-E_{DG}(t)-E^{buy}-min\left(E_{inv}^{max},\eta_{inv}E_{\Re}\right)Ens_{DC}(t)=\frac{Ens_{AC}(t)}{\eta_{inv}} \quad \text{[kWh]} \quad (22)$$

Second scenario: If C_{buy} is lower than $cost_{BT}^{Wear}$ *and* $cost_{BT}^{Wear}$ is lower than $cost_{DG}$, it is more cost effective to first buy the unsatisfied load (Ens_{AC}) from the grid using Eq.17, and then discharge the batteries using Eq.20. However, in this scenario, for calculating the Ens_{DC} in Eq.20, Eq.23 should be used. If there is still unsatisfied load, at the last step, diesel generators can be operated using Eq.24 and Eq.19. In this equation, $Ens_{AC}(t)$ can be calculated from Eq. 25.

$$Ens_{DC}(t) = min\left(\frac{E_{inv}^{max}}{\eta_{inv}}, \frac{E_{load}(t) - E^{buy}}{\eta_{inv}} - E_{\Re}\right) \quad \text{[kWh]} \quad (23)$$

$$E_{DG}(t) = min\left(Ens_{AC}(t), E_{DG}^{rated}\right) \quad \text{[kWh]} \quad (24)$$

$$Ens_{AC}(t) = E_{load}(t) - E^{buy} - min¿¿ \quad \text{[kWh]} \quad (25)$$

Third scenario: If the $cost_{DG}$ is lower than C_{buy} and C_{buy} is lower than $cost_{BT}^{Wear}$, the first priority for satisfying the remaining load will be given to DG operated based on Eq.24 and Eq.19. If DG cannot meet the remaining load, electricity can be bought from the grid using Eq.26. If DG generates more than what is needed, it can be sold to the grid using Eq.27. Batteries in this scenario have the last priority and can be discharged using Eq.20, using the Ens_{DC} formula mentioned in Eq.28.

$$E^{buy} = max\ ¿) \quad \text{[kWh]} \quad (26)$$

$$E^{sell} = max\ ¿ \quad \text{[kWh]} \quad (27)$$

$$Ens_{DC}(t) = min\left(\frac{E_{inv}^{max}}{\eta_{inv}}, \frac{E_{load}(t) - E_{DG} - E^{buy}}{\eta_{inv}} - E_{\Re}\right) \quad \text{[kWh]} \quad (28)$$

Fourth scenario: If the $cost_{DG}$ is lower than $cost_{BT}^{Wear}$ and $cost_{BT}^{Wear}$ is lower than C_{buy}, then the priority for generating the unsatisfied electricity load will be for DG using Eq.24 and Eq.19. The second priority for satisfying the load will be based on discharging the batteries using Eq.20 and Ens_{DC} formula calculated using Eq.29. The last priority will be given to the grid for interconnection using Eq.26 and Eq.27.

$$Ens_{DC}(t) = min\left(\frac{E_{inv}^{max}}{\eta_{inv}}, \frac{E_{load}(t) - E_{DG}}{\eta_{inv}} - E_{\Re}\right) \quad \text{[kWh]} \quad (29)$$

Fifth scenario: If the $cost_{BT}^{Wear}$ is lower than $cost_{DG}$, and $cost_{DG}$ is less than C_{buy}, it is more economic to first discharge the batteries and for the remaining unsatisfied load use Eq.20 based on Ens_{DC} mentioned in Eq.30. As the second priority, DG can operate using Eq.24 and Eq.19 based on Ens_{AC} calculated using Eq.31, and if DG cannot satisfy the load, using equations 26 and 27, the energy system can operate with grid electricity.

$$Ens_{DC}(t)=min\left(\frac{E_{inv}^{max}}{\eta_{inv}},\frac{E_{load}(t)}{\eta_{inv}}-E_{\Re}\right) \quad \text{[kWh]} \quad (30)$$

$$Ens_{AC}(t)=E_{load}(t)-min¿¿ \quad \text{[kWh]} \quad (31)$$

Sixth scenario: If scenarios 1-5 are not met, it means that the first priority will be given to discharging the batteries, second will be given to interconnecting to the grid and last one will be given to the DG. Therefore, batteries should be discharged based on Eq.20 and Ens_{DC}mentioned in Eq.30. If they are not enough, system should buy the electricity from the grid using Eq.32. $Ens_{AC}(t)$ in Eq.32 can be calculated from Eq.33. If buying the entire remaining load is not fully applicable from the grid, then DG should operate using Eq.18 and Eq.24.

$$E^{buy}(t)=min\left(Ens_{AC}(t),E^{buy,max}\right) \quad \text{[kWh]} \quad (32)$$

$$Ens_{AC}(t)=E_{load}(t)-min\ ¿ \quad \text{[kWh]} \quad (33)$$

In each time-step (t) and for all operations, not satisfied load on DC side in kWh ($ENS_{DC}(t)$) is calculated using the Eq.34. If $Ens_{DC}$is negative, then again battery can be charged again using Eq.35, otherwise, the total dumped energy in system (E_{Dump}) is calculated from Eq.36.

$$Ens_{DC}=min\left(\frac{E_{inv}^{max}}{\eta_{inv}},\frac{E_{load}(t)+E^{sell}-E_{DG}-E^{buy}}{\eta_{inv}}\right)-E_{\Re}+E_{BT}^{dch}-E_{BT}^{ch} \quad \text{[kWh]} \quad (34)$$

$$E_{BT}^{ch}(t)=min\left(E_{BT}^{empty},E_{BT}^{ch}(t)-ENS_{DC}(t)\right)\wedge ¿\, E_{BT}^{ch}(t)=\min\ (E_{BT}^{ch}(t),E_{BT,ch}^{max}) \quad \text{[kWh]} \quad (35)$$

$$E_{Dump}(t)=min\left(E_{inv}^{max},\left(E_{\Re}(t)+E_{BT}^{dch}(t)-E_{BT}^{ch}(t)\right)\times\eta_{inv}\right)+E_{DG}(t)-E_{load}(t)¿ \quad \text{[kWh]} \quad (36)$$

Finally, total energy stored [kWh] in battery bank for the next time-step ($E_{BT}(t+1)¿$ is determined using Eq.37 and EMS will be run for all simulation time-steps.

$$E_{BT}(t+1)=(1-\delta)\times E_{BT}(t)+\eta_{BT}\times E_{BT}^{ch}(t)-\frac{E_{BT}^{dch}(t)}{\eta_{BT}} \quad \text{[kWh] (37)}$$

The flowchart EMS based on the above discussions is shown in Fig.3.

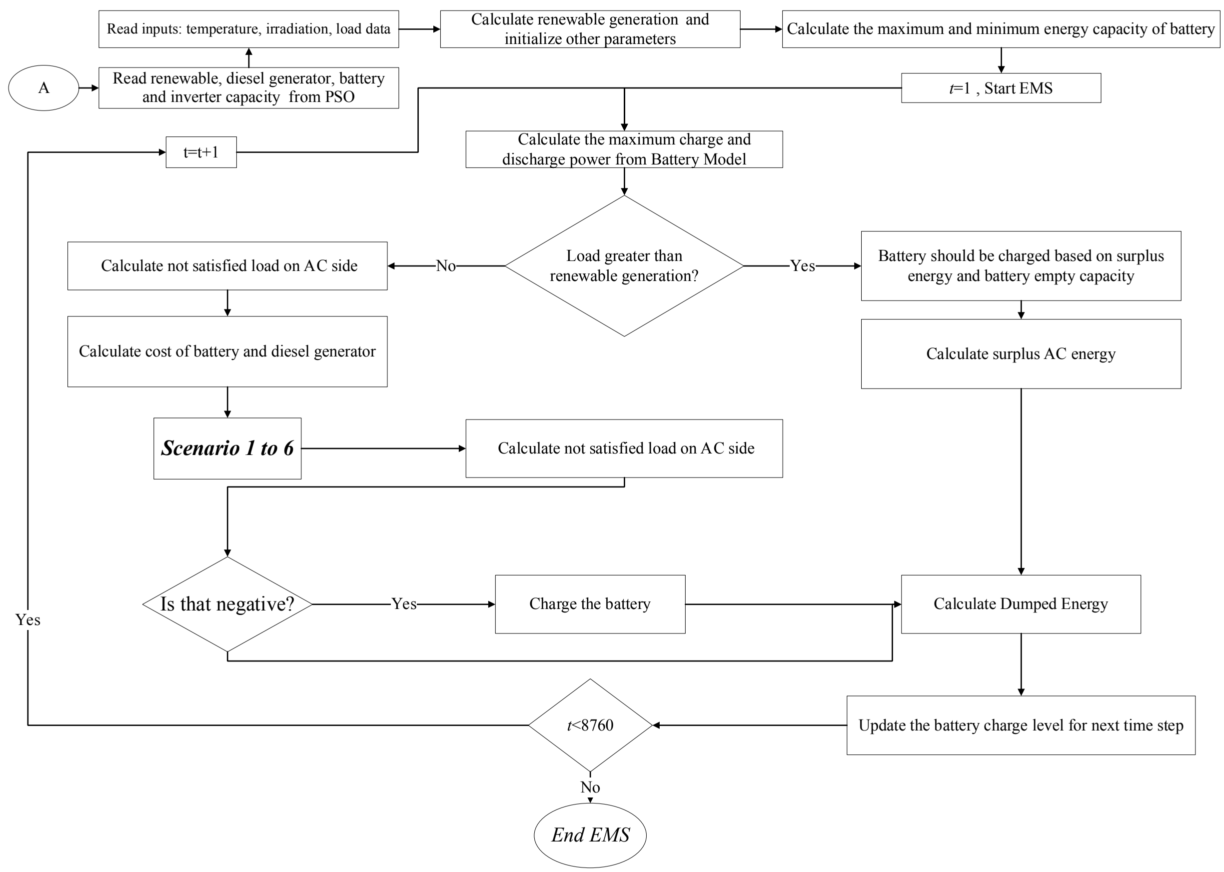

Fig.3. EMS algorithm.

The EMS pseudo-code is attached below:

FUNCTION EMS(Ppv, Pwt, Eload, Cn_B, Nbat, Pn_DG, NT, SOC_max, SOC_min, SOC_initial, n_I, Grid, Cbuy, a, Pinv_max, LR_DG, C_fuel, Pbuy_max, Psell_max, cc_gen, Cbw, self_discharge_rate, alfa_battery, c, k, Imax, Vnom, ef_bat)
// Initialize arrays for power and energy variables
Eb, Pch, Pdch, Pdg, Edump, Ens, Psell, Pbuy, Pinv are arrays of size NT (total hours in a year)
// Set initial battery energy
Eb[1] = SOC_initial * Cn_B
// Set maximum and minimum energy stored in the battery
Ebmax = SOC_max * Cn_B
Ebmin = SOC_min * Cn_B
// Time step (assumed to be 1 hour)
dt = 1
// Set maximum buy and sell power to zero if there's no grid connection

```
IF Grid is 0 THEN
   Pbuy_max = 0
   Psell_max = 0
ENDIF
// Renewable energy power is the sum of PV and wind turbine power
P_RE = Ppv + Pwt
// Set minimum diesel generator power based on renewable power availability
IF sum(Ppv + Pwt + Pbuy) is 0 THEN
   Pdg_min = 0.25 * Pn_DG  // Load Ratio of DG (LR_DG)
ELSE
   Pdg_min = 0
ENDIF
// Start the main loop over time
FOR t in 1 to NT DO
   // Get the maximum charging and discharging power of the battery from Battery Model
   [Pch_max, Pdch_max] = Battery_Model(Cn_B, Nbat, Eb[t], alfa_battery, c, k, Imax, Vnom, ef_bat)
   // If renewable power is greater than load (battery should charge)
   IF P_RE[t] >= Eload[t] / n_I THEN
      // Calculate battery charge power based on surplus energy and battery empty capacity
      Eb_e = (Ebmax - Eb[t]) / sqrt(ef_bat)
      Pch[t] = min(Eb_e, P_RE[t] - Eload[t] / n_I)
      // Limit battery charge power to its maximum
      Pch[t] = min(Pch[t], Pch_max)
      // Calculate surplus AC power
      Psur_AC = n_I * (P_RE[t] - Pch[t]) - Eload[t]
      // Limit sell power to its maximum and inverter power
      Psell[t] = min(Psur_AC, Psell_max)
      Psell[t] = min(max(0, Pinv_max - Eload[t]), Psell[t])
      // Calculate dumped energy
      Edump[t] = P_RE[t] - Pch[t] - (Eload[t] + Psell[t]) / n_I
   // If load is greater than renewable power
   ELSE
      // Calculate deficit AC energy
      Edef_AC = Eload[t] - min(Pinv_max, n_I * P_RE[t])
      // Determine the price of diesel generator
      price_dg = cc_gen + a * C_fuel
      // Depending on the electricity prices, choose the optimal operation
      // (1) Grid, DG, Bat: Grid is the cheapest, then DG, then Battery
      IF (Cbuy[t] <= price_dg) AND (price_dg <= Cbw) THEN
         Pbuy[t] = min(Edef_AC, Pbuy_max)
         Pdg[t] = min(Edef_AC - Pbuy[t], Pn_DG)
           Pdg(t)=Pdg(t)*(Pdg(t)>=LR_DG*Pn_DG)
+LR_DG*Pn_DG*(Pdg(t)<LR_DG*Pn_DG)*(Pdg(t)>Pdg_min)
         Edef_AC = Eload[t] - Pdg[t] - Pbuy[t] - min(Pinv_max, n_I * P_RE[t])
         Edef_DC = Edef_AC / n_I * (Edef_AC > 0)
         Eb_e = (Eb[t] - Ebmin) * sqrt(ef_bat)
         Pdch[t] = min(Eb_e, Edef_DC)
         Pdch[t] = min(Pdch[t], Pdch_max)
         Esur_AC = -Edef_AC * (Edef_AC < 0)
         Pbuy[t] = Pbuy[t] - Esur_AC * (Grid == 1)
      // (2) Grid, Bat, DG: Grid is the cheapest, then Battery, then DG
      ELSE IF (Cbuy[t] <= Cbw) AND (Cbw < price_dg) THEN
         Pbuy[t] = min(Edef_AC, Pbuy_max)
         Edef_DC = (Eload[t] - Pbuy[t]) / n_I - P_RE[t]
         Eb_e = (Eb[t] - Ebmin) * sqrt(ef_bat)
         Pdch[t] = min(Eb_e, Edef_DC)
```

```
            Pdch[t] = min(Pdch[t], Pdch_max)
            Edef_AC = Eload[t] - Pbuy[t] - min(Pinv_max, n_I * (P_RE[t] + Pdch[t]))
            Pdg[t] = min(Edef_AC, Pn_DG)
              Pdg(t)=Pdg(t)*(Pdg(t)>=LR_DG*Pn_DG)
+LR_DG*Pn_DG*(Pdg(t)<LR_DG*Pn_DG)*(Pdg(t)>Pdg_min)
        // (3) DG, Grid, Bat: DG is the cheapest, then Grid, then Battery
        ELSE IF (price_dg < Cbuy[t]) AND (Cbuy[t] <= Cbw) THEN
            Pdg[t] = min(Edef_AC, Pn_DG)
              Pdg(t)=Pdg(t)*(Pdg(t)>=LR_DG*Pn_DG)
+LR_DG*Pn_DG*(Pdg(t)<LR_DG*Pn_DG)*(Pdg(t)>Pdg_min)
            Pbuy[t] = max(0, min(Edef_AC - Pdg[t], Pbuy_max))
            Psell[t] = max(0, min(Pdg[t] - Edef_AC, Psell_max))
            Edef_DC = (Eload[t] - Pbuy[t] - Pdg[t]) / n_I - P_RE[t]
            Edef_DC = Edef_DC * (Edef_DC > 0)
            Eb_e = (Eb[t] - Ebmin) * sqrt(ef_bat)
            Pdch[t] = min(Eb_e, Edef_DC)
            Pdch[t] = min(Pdch[t], Pdch_max)
        // (4) DG, Bat, Grid: DG is the cheapest, then Battery, then Grid
        ELSE IF (price_dg < Cbw) AND (Cbw < Cbuy[t]) THEN
            Pdg[t] = min(Edef_AC, Pn_DG)
              Pdg(t)=Pdg(t)*(Pdg(t)>=LR_DG*Pn_DG)
+LR_DG*Pn_DG*(Pdg(t)<LR_DG*Pn_DG)*(Pdg(t)>Pdg_min)
            Edef_DC = (Eload[t] - Pdg[t]) / n_I - P_RE[t]
            Edef_DC = Edef_DC * (Edef_DC > 0)
            Eb_e = (Eb[t] - Ebmin) * sqrt(ef_bat)
            Pdch[t] = min(Eb_e, Edef_DC)
            Pdch[t] = min(Pdch[t], Pdch_max)
            Edef_AC = Eload[t] - Pdg[t] - min(Pinv_max, n_I * (P_RE[t] + Pdch[t]))
            Pbuy[t] = max(0, min(Edef_AC, Pbuy_max))
            Psell[t] = max(0, min(-Edef_AC, Psell_max))
        // (5) Bat, DG, Grid: Battery is the cheapest, then DG, then Grid
        ELSE IF (Cbw < price_dg) AND (price_dg < Cbuy[t]) THEN
            Edef_DC = Eload[t] / n_I - P_RE[t]
            Eb_e = (Eb[t] - Ebmin) * sqrt(ef_bat)
            Pdch[t] = min(Eb_e, Edef_DC)
            Pdch[t] = min(Pdch[t], Pdch_max)
            Edef_AC = Eload[t] - min(Pinv_max, n_I * (P_RE[t] + Pdch[t]))
            Pdg[t] = min(Edef_AC, Pn_DG)
              Pdg(t)=Pdg(t)*(Pdg(t)>=LR_DG*Pn_DG)
+LR_DG*Pn_DG*(Pdg(t)<LR_DG*Pn_DG)*(Pdg(t)>Pdg_min)
            Pbuy[t] = max(0, min(Edef_AC - Pdg[t], Pbuy_max))
            Psell[t] = max(0, min(Pdg[t] - Edef_AC, Psell_max))
        // (6) Bat, Grid, DG: Battery is the cheapest, then Grid, then DG
        ELSE
            Edef_DC = min(Pinv_max, Eload[t] / n_I) - P_RE[t]
            Eb_e = (Eb[t] - Ebmin) * sqrt(ef_bat)
            Pdch[t] = min(Eb_e, Edef_DC) * (Edef_DC > 0)
            Pdch[t] = min(Pdch[t], Pdch_max)
            Edef_AC = Eload[t] - min(Pinv_max, n_I * (P_RE[t] + Pdch[t]))
            Pbuy[t] = min(Edef_AC, Pbuy_max)
            Pdg[t] = min(Edef_AC - Pbuy[t], Pn_DG)
              Pdg(t)=Pdg(t)*(Pdg(t)>=LR_DG*Pn_DG)
+LR_DG*Pn_DG*(Pdg(t)<LR_DG*Pn_DG)*(Pdg(t)>Pdg_min)
        ENDIF

        Edef_DC = (Eload[t] + Psell[t] - Pdg[t] - Pbuy[t]) / n_I - (P_RE[t] + Pdch[t] - Pch[t])
```

```
      IF Edef_DC < 0 THEN
        Eb_e = (Ebmax - Eb[t]) / sqrt(ef_bat)
        Pch[t] = min(Eb_e, Pch[t] - Edef_DC)
        Pch[t] = min(Pch[t], Pch_max)
      ENDIF

      Esur = Eload[t] + Psell[t] - Pbuy[t] - Pdg[t] - min(Pinv_max, (P_RE[t] + Pdch[t] - Pch[t]) * n_I)
      Ens[t] = Esur if Esur > 0 else 0
      Edump[t] = -Esur if Esur < 0 else 0
    ENDIF

    // Update battery charging and discharging energy and battery charge level
    Ech[t] = Pch[t] * dt
    Edch[t] = Pdch[t] * dt
    Eb[t + 1] = (1 - self_discharge_rate) * Eb[t] + sqrt(ef_bat) * Ech[t] - Edch[t] / sqrt(ef_bat)
  ENDFOR

  RETURN [Eb, Pdg, Edump, Ens, Pch, Pdch, Pbuy, Psell, Pinv]
ENDFUNCTION
```

4.14 *Economic modeling*

4.14.1 Pricing methodology

SAMA uses two different methodologies for equipment pricing in the hybrid energy system. The novel methodology for pricing introduced in SAMA is ***Top-down pricing methodology*** which considers the total PV system costs per kW ($C_{PVsystem}^{Total}$¿ and then for other parts of energy system, tries to break down the $C_{PVsystem}^{Total}$ using NREL percentages mentioned in the NREL PV benchmark for 2022 [3]. This pricing definition is easy to use for ordinary users and also will give this opportunity to researchers to conduct sensitivity analysis on the $C_{PVsystem}^{Total}$. Using the Top-down method, ordinary users will not need to deal with the pricing in the system and can use the default values and rates published by NREL [3]. Another pricing methodology defined in SAMA is ***Bottom-up pricing*** definition, similar to other software pricing method such as Homer Pro. In this methodology, user needs to input all the breakdown prices of parts in the energy system such as capital cost, replacement cost and operation and maintenance cost separately and one by one. This pricing method will contribute more accurate economic result while more complexity for users to find and add the costs to the software.

4.14.2 Economic analysis

Economic assessment is an essential step towards analyzing feasibility of hybrid energy systems. Hybrid systems can economically analyzed using Net Present Cost (*NPC*). Before calculating the *NPC*, SAMA calculates real discount rate (*i*) based on Eq.38 using nominal discount rate (*i'*) and inflation rate (*f*). Now having the real discount rate value, *NPC* can be calculated using Eq. 39 [57] which is the summation of total investment cost (C_I) at the beginning of the project (Eq.40) [8], plus sum of present values (over the life time of project (*n*)) of total replacement cost (Eq.41) (C_R), total maintenance and operation costs calculated by Eq.42 (C_{MO}) [8], total fuel costs (C_F) calculated by Eq.43, total salvages costs (Eq.44) (C_S) [58], and total grid cost (Eq.45) (C_G).

$$i=\frac{i^{'}-f}{1+f} \tag{38}$$

$$NPC=C_I+\frac{C_R+C_{MO}+C_F-C_S+C_G}{(1+i)^n}$$

(39)

$$C_I=C_{PV}P_{PV}^{total}+C_{DG}P_{DG}^{total}+C_{BT}N_{total}^{BT}+C_{Inv}P_{Inv}+C_{CH}+C_{Eng} \tag{40}$$

$$C_R=C_{PV}^{R}P_{PV}^{total}+C_{DG}^{R}P_{DG}^{total}+C_{BT}^{R}N_{total}^{BT}+C_{Inv}^{R}P_{Inv}+C_{CH}^{R} \tag{41}$$

$$C_{MO}=C_{PV}^{MO}P_{PV}^{total}+C_{DG}^{MO}P_{DG}^{total}+C_{BT}^{MO}N_{total}^{BT}+C_{Inv}^{MO}P_{Inv}+C_{CH}^{MO} \tag{42}$$

$$C_F=\sum_{0}^{8760} Fuel\,cost\,per\,liter\,q \tag{43}$$

$$C_S=S_{PV}+S_{DG}+S_{BT}+S_{inv}+S_{CH}\in which\,S_{comp}=R_{comp}\frac{n_{rem}}{n_{comp}} \tag{44}$$

$$C_G=C_{Grid}^{¿,Annual}+\sum_{0}^{12}C_{Grid}^{¿,monthly}+\sum_{0}^{8760}C_{buy}P_{buy}-\sum_{0}^{8760}C_{sell}P_{sell} \tag{45}$$

In equation 40, C_{PV} is the capital cost of PV modules [$/kW] and P_{PV}^{total} is total capacity of PV modules [kW], C_{DG} is the capital cost of diesel generator [$/kW] and $P_{DG}^{total}$is the capacity of DG, C_{BT} is the capital cost of battery [$/kWh] and $N_{¿tal}^{BT}$ is the total capacity of battery storage bank,

C_{Inv} is the inverter capital cost [$/kW] and P_{Inv} is the inverter capacity [kW], C_{CH} is the price of battery charger and C_{Eng} is the engineering costs. Engineering costs includes Installation cost, Overhead costs, Sales and marketing, Permitting and Inspection, Electrical BoS, Structural BoS, Sales tax, Supply Chain costs and profits. This data are extracted from NREL PV benchmark for 2022 [3].

In equation 41, C_{PV}^{R}, C_{DG}^{R}, C_{BT}^{R}, C_{inv}^{R}, $C_{CH}^{R}$are the replacement costs [$/kW] of the PV, DG, battery, inverter and charger, respectively. In equation 42, C_{PV}^{MO}, C_{DG}^{MO}, C_{BT}^{MO}, C_{inv}^{R}, $C_{CH}^{R}$are the maintenance and operation costs [$/kW] of the PV, DG, battery, inverter and charger, respectively. S_{PV}, S_{DG}, S_{inv}, and S_{CH} in equation 44 represent the salvage costs of PV, DG, inverter and charger, respectively.

Equation 45, shows the formula for calculating total grid cost through a year, in which $C_{Grid}^{\text{¿},Annual}$ is the fixed annual grid costs, $C_{Grid}^{\text{¿},monthly}$ is the fixed monthly service charges, C_{buy} is the hourly cost of buying electricity from grid [$/kWh] (discussed in the utilities structures section (2.5.6) and P_{buy} is power bought from the grid in each hour [kWh/h], C_{sell} is per kW fixed sellback electricity price to the grid [$/kW] and P_{sell} is the power sold to the grid in each hour [kWh].

4.15 Optimization Strategy

4.7.1 Optimization objectives

4.7.1.1 Levelized cost of electricity (LCOE)

LCOE is the first objective for optimizations. It refers to the average cost of producing electricity over the lifetime of the system in $/kWh, taking into account all costs associated with the system's installation, operation, and maintenance. To determine the LCOE, the initial step for SAMA involves computing the capacity recovery factor (*CRF*) using Equation 46 [59]. This equation calculates the annual payment needed to recoup the initial capital investment within a designated lifetime.

$$CRF(i,N)=\frac{i(1+i)^{n}}{(1+i)^{n}-1} \tag{46}$$

After calculating *CRF*, SAMA calculates *LCOE* as follows [59]:

$$LCOE = \frac{CRF\,NPC}{\sum_{0}^{8760} \left(Eload - Ens + P_{sell}\right)}$$ [$/kWh]

(47)

SAMA also calculates operating costs using Eq.48 referring to the aggregated value of all expenses and income, excluding the initial capital investment, on an annual basis.

$$Operating\,Cost = CRF\left(C_R + C_{MO} + C_F - C_S + C_G\right)$$ (48)

4.7.1.2 Levelized Emission (LE)

To optimize emission levels for a system, SAMA, uses a concept called levelized emission (LE). This concept is similar to what presented in Parlikar *et al.* [60] paper for levelized emissions. Eq.49 represents the formula for LE.

¿ $$= \frac{\sum_{0}^{8760} Non\,Grid\ Emissions(t) + \sum_{0}^{8760} Grid_{Emissions}(t)}{\sum_{0}^{8760} \left(E_{load}(t) - Ens(t)\right)}$$ [kg/kWh](49)

Where $Non\,Grid\ Emissions$ is the emission produced form non grid energy sources calculated from Eq.50. In SAMA current stage, Eq.50 is only exhibits DG ($\left(Non\,Grid\ Emissions\right)_{Others}$¿, in which q is the fuel consumption of DG calculated from Eq.51. $EF_{non\ grid}$ is the emission produced by consuming each liter of fuel (kg/liter), P_{DG} is the power generated by DG in each hour, and $P_{DG}^{Nominal}$ is the total rated power of all DGs in the system.

$$Non\,Grid\ Emissions = \left(q\,EF_{non\,grid}\right)_{DG} + \left(Non\ Grid\ Emissions\right)_{Others}$$ [kg] (50)

$$q = a\,P_{DG} + b\,P_{DG}^{Nominal}$$ [Liter] (51)

Emission produced by the grid is also considered in SAMA and is calculated from Eq.52, in which E_{buy} is the electricity bought from the grid in each hour in kWh, and EF_{Grid} is the emission produced by the grid in kg by buying each kWh [kg/kWh].

$$Grid\ Emissions = E_{buy}\, EF_{Grid} \qquad [\mathrm{kg}] \quad (52)$$

4.7.2 Optimization flowchart

The flowchart of the optimization strategy used in SAMA is shown in Fig.4. SAMA optimizes for the Net Present Cost (*NPC*), while also considering some constraints to limit power loss, using fossil fuels and capital cost. Hence, SAMA allows users to set a maximum for loss of power supply probability (*LPSP*), renewable fraction (*RF*) and budget. It also gives the user the option of considering emissions in optimizations using the novel concept defined as levelized emissions (*LE*). The final results in SAMA are a hybrid energy system with optimum size while minimizing emissions as well.

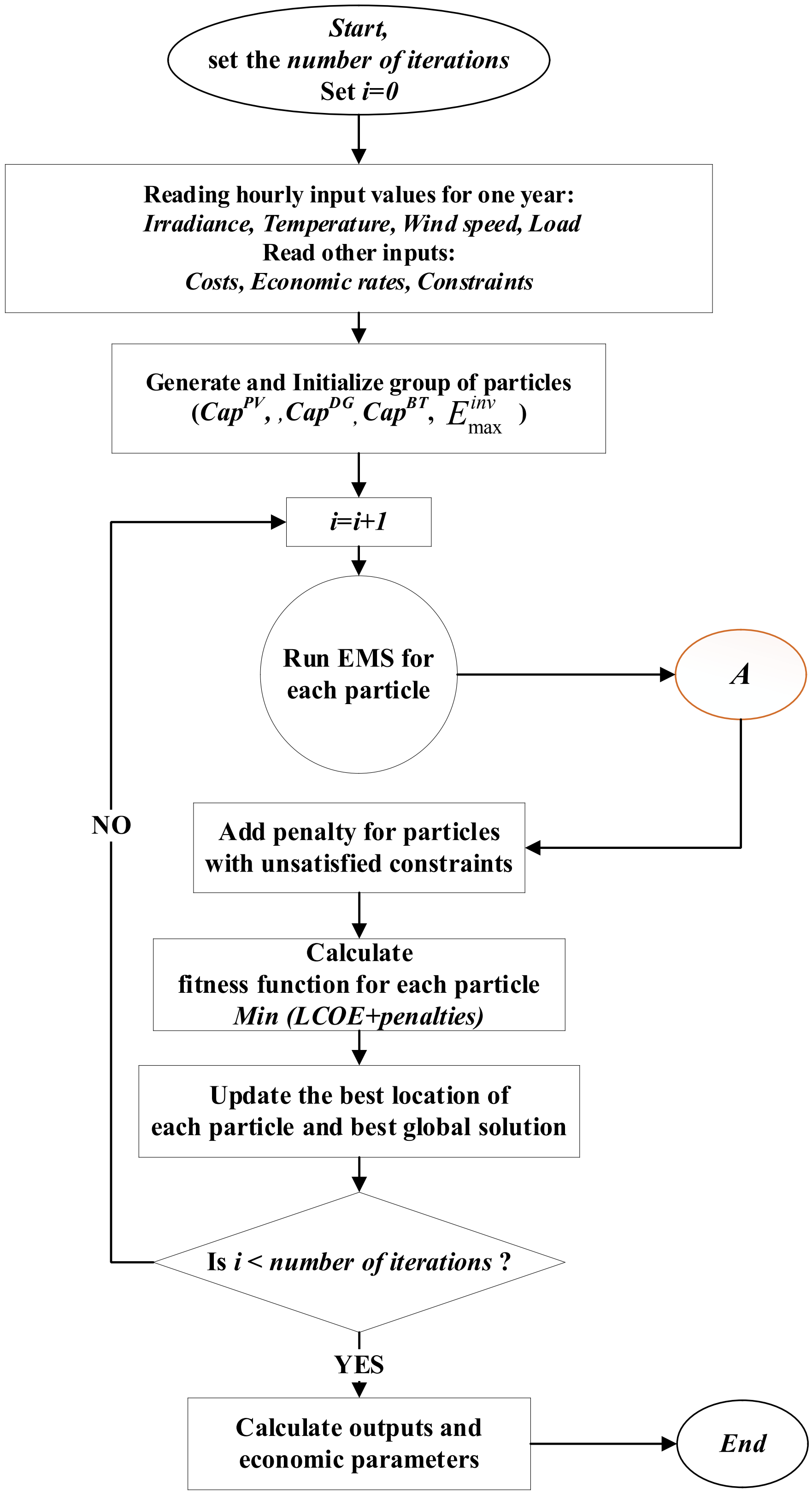

Fig.4. Optimization algorithm

4.7.3 Optimization constraints

Three constraints are defined for the objective function: First constraint is the user maximum budget for total capital cost of system. The two other important constraints are maximum loss of power supply probability ($LPSP_{max}$) and renewable fraction (*RF*). The LPSP is a measure of how acceptable for the user is it to not have continuous power. In general, users willing to forgo power for longer periods will have access to lower capital cost systems. *LPSP* is assigned to the objective function due to uncertainty in PV power production, and defined as the deficits to the total load demand for one year [61], [62]. In Eq.53, *Ens(t)* is the not satisfied load in each hour in kW and E_{load} is the electricity load for each hour in kW.

$$LPSP=\frac{\sum_{t}^{8760} Ens(t)}{\sum_{t}^{8760} E_{load}(t)} \tag{53}$$

The percentage of energy demand that is satisfied by renewable sources is known as *RF*. *RF* can be calculated from Eq.54 [14].$E_{non\,renewable}(t)$ is the energy produced by non-renewable sources such as diesel generator (DG) in each hour.

$$RF=1-\frac{\sum_{t}^{8760} E_{nonrenewable}(t)}{\sum_{t}^{8760} (E¿¿load(t)-ENS(t))¿¿}$$

(54)

4.7.4 Multi objective function for optimization

The multi objective function (*Z*) for optimizations in SAMA is stated in equation below:

$$Z=NPC+EM\leq+penalties \tag{55}$$

If constraints are not met in optimizations, SAMA optimizer applies penalties to the objective function in order to reach the optimum value. These penalties are discussed in Table.2.

Table.2. Types of penalties in SAMA optimizations

Penalties	Reason
$P_{PV}^{Nominal} > 1.99 (P ¿¿ Inv^{Nominal} + P_{DG}^{Nominal} + P_{buy}^{max}) ¿$	DC to AC ratio should be less than 2. If a system is sized with DC to AC ratio of higher than 2, it should not be considered as optimum solution.
$LPSP > LPSP_{max}$	If energy systems are not able to provide enough power to the load
$\Re < RE_{min}$	If energy systems rely more on non-renewable sources than what is considered as limit
$I_{Cost} > Budget$	If initial cost of system is higher than what is preferred by user

5 Software Validation

The results generated by the SAMA software were cross-verified with those obtained from Homer Pro, a well-established and widely recognized tool in this domain. This comparison was conducted across two distinct geographical locations with different climate conditions, namely Sacramento California and New Bern North Carolina in the U.S. In optimizations using PSO algorithm, the maximum number of iterations is considered 101 with population size of 100 while the simulations were repeated 10 times to assess convergence of optimization algorithm. Fig. 5 illustrates Sacramento (Fig.5a) and New Bern (Fig.5b) case studies' convergence curves for 10 repeated runs. This figure pointing to the fact that for first run the optimizer reaches a convergence point after iteration 70, while for next runs, the convergence has been reached even sooner (after iteration 20). To ensure consistency, both software programs were configured to use the same input data shown in Table 1. It should be noted that due to difference in pricing methodologies in the two software packages and pricing rounding in Homer Pro slight difference in final results are expected. For validation purposes, top-down pricing method in SAMA, (discussed in section 4) is used. On the other hand, Homer Pro uses a pricing methodology similar to bottom-up method mentioned in section 4. All prices from SAMA top-down calculations were converted to Homer Pro which is only considers two decimal digits. For both SAMA and Homer Pro, Sacramento and New Bern's residential electrical load data are extracted from OpenEI database [2]. The *POA* along with other meteorological data for SAMA simulations were extracted from Homer Pro based on its access to NREL for solar data and NASA prediction of Worldwide Energy Resources for temperature. The pricing methodology considered in SAMA for comparison is top-down method which Homer Pro does not have. Therefore, all the prices were converted to be the same as SAMA for Homer Pro. The grid hourly purchase price (C_{buy}) for both Sacramento and New Bern is defined in SAMA based on the information on their websites, respectively [32], [63]. The real-time prices were extracted from SAMA and were used for Homer Pro as well.

A comprehensive comparison of the final outputs from different types of energy systems is presented in Table 3 (Sacramento, CA results) and Table 4 (New Bern, North Carolina results). Upon close examination, it becomes apparent that the final results yielded by SAMA are strikingly similar to those of Homer Pro. Fig.6 and Fig.7 present a comprehensive comparison of the different hourly outputs from SAMA alongside those from Homer Pro for Sacramento and New Bern, respectively. As it is obvious from Fig.6a and Fig.7a, both SAMA and Homer Pro PV power generation yields almost same values. For DG output in Fig.6b and Fig.7b, both software packages are following same trends while slight differences exist. These differences show that SAMA is more open to use DG in order to reduce the loss of power supply as much as possible. According to the Fig.6c and Fig.7c as well as Fig.6d and Fig.7d, energy storage system behave almost same in both SAMA and Homer Pro. Fig.6e and Fig.7e verifies this claim while illustrating that SAMA is charging batteries more. Also, Fig. 8 demonstrate SAMA's 1st and 180th day of year result for Sacramento; one is a cold day of year with low levels of irradiation and another one exhibiting higher temperatures and irradiations. Fig. 9 demonstrates the same results for New Bern case study. First day of year is experiencing lower levels of irradiation, and as the result PV output will be lower. Therefore SAMA tries to use DG to satisfy the remained demand. This higher output in 180th day of year will result in higher battery energy levels and dumped energy compared to first day of year. Further SAMA outputs for Sacramento and New Bern are reported in Appendix in Fig.A1 to Fig.A14.

Despite the overall congruence, minor discrepancies do exist between the software packages, attributable primarily to the distinct dispatch strategies, pricing methodologies, and the inevitable rounding that occurs during calculations. Both SAMA and Homer Pro implement the load following strategy for energy management and distribution, formerly referred to as EMS. It is important to note, however, that SAMA's approach to the load following strategy has been uniquely developed from scratch, focusing more diligently on finding optimum/cost effective systems with lower power shortages. Moreover, SAMA's top-down pricing method, discussed in detail in a section 4, differs from that used by Homer Pro. These inherent distinctions between the software can reasonably account for the slight variation in their outputs.

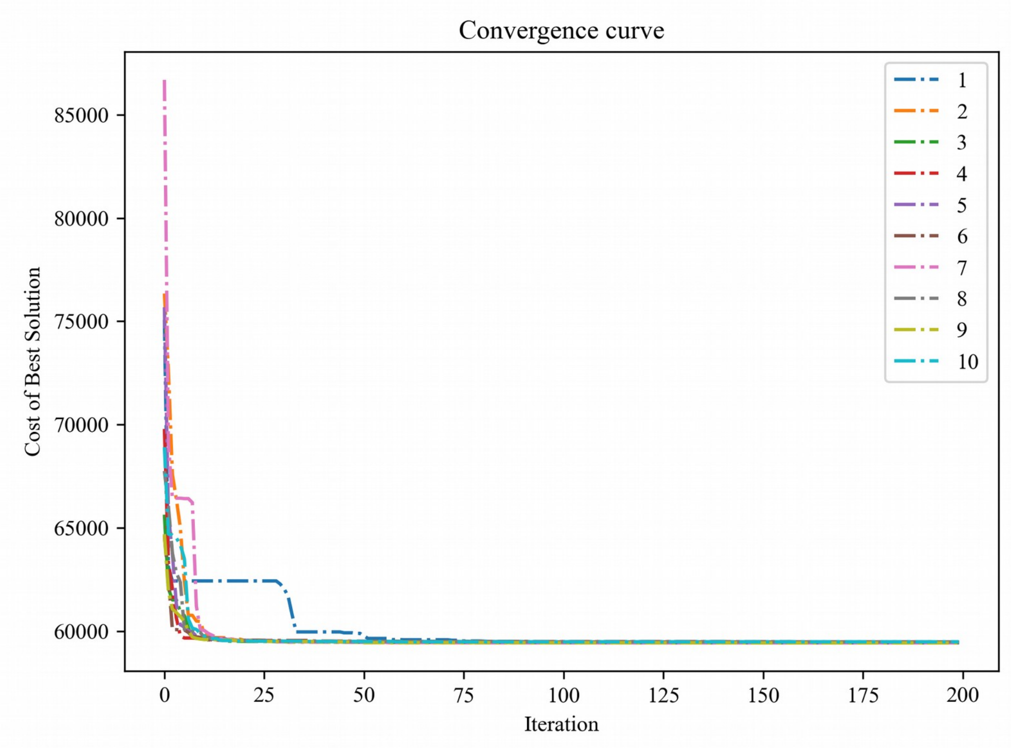

Fig.5a. Optimization convergence curves for the Sacramento, CA case.

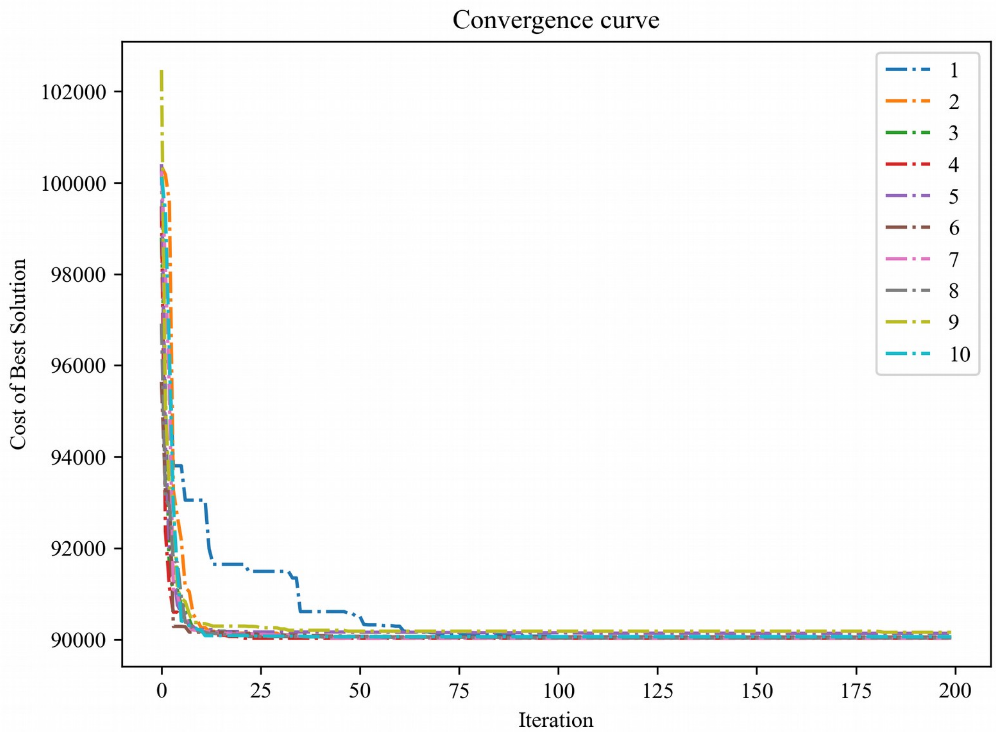

Fig.5b. Optimization convergence curves for the New Bern, NC case.

Table 3. Comparison of different energy systems results (SAMA & Homer Pro)-Sacramento, CA.

System type		System Size				LCOE [$/kWh]	NPC [$]	Initial cost [$]	Operating Cost [$]	O&M cost [$]	RE (%)	LPSP (%)	Excess Electricity [kWh/yr]	PV energy [kWh/yr]	DG energy [kWh/yr]	Battery energy In [kWh/yr]	Battery energy Out [kWh/yr]	Grid Sell [kWh/yr]	Grid Buy [kWh/yr]
		PV [kW]	DG [kW]	BT [kWh]	Inv [kW]														
SAMA	PV+Grid	8.47	0	0	7.24	0.0838	30246	17133	708	4945	75	0	162	15376	0	0	0	10736	4869
	PV+BT+Grid	8.47	0	0	7.24	0.0838	30246	17133	708	4945	75	0	162	15376	0	0	0	10736	4869
	PV+BT+DG+Grid	8.47	0	0	7.24	0.0838	30246	17133	708	4945	75	0	162	15376	0	0	0	10736	4869
	PV+BT+DG	**7.31**	**1.67**	**19**	**2.95**	**0.3674**	**59426**	**20539**	**2099**	**11291**	**85.4**	**0.09951**	**4457**	**13275**	**1272**	**4918**	**3939**	**0**	**0**
	PV+BT	17.02	0	79	8.55	0.9170	148331	58745	4835	24650	100	0.09999	20592	30901	0	5896	4707	0	0
Homer Pro	PV+Grid	8.45	0	0	7.51	0.0843	30472	17304	704	4948	75	0	92.1	15336	0	0	0	10766	4870
	PV+BT+Grid	8.52	0	0	7.29	0.0841	30479	17363	708	4974	75.1	0	161	15469	0	0	0	10822	4865
	PV+BT+DG+Grid	8.52	0	0	7.29	0.0841	30479	17363	708	4974	75.1	0	161	15469	0	0	0	10822	4865
	PV+BT+DG	**7.25**	**1.7**	**20**	**2.90**	**0.373**	**60342**	**20605**	**2145**	**11564**	**85.3**	**0.0758**	**4446**	**13165**	**1283**	**4826**	**3866**	**0**	**0**
	PV+BT	16.6	0	82	8.46	0.920	148831	58283	4887	24990	100	0.0995	19928	30213	0	5907	4716	0	0

Table 4. Comparison of different energy systems results (SAMA & Homer Pro)-New Bern.

System type		System Size PV [kW]	DG [kW]	BT [kWh]	Inv [kW]	LCOE [$/kWh]	NPC [$]	Initial cost [$]	Operating Cost [$]	O&M cost [$]	RE (%)	LPSP (%)	Excess Electricity [kWh/yr]	PV energy [kWh/yr]	DG energy [kWh/yr]	Battery energy In [kWh/yr]	Battery energy Out [kWh/yr]	Grid Sell [kWh/yr]	Grid Buy [kWh/yr]
SAMA	PV+Grid	13.63	0	0	11.39	0.0759	39796	27490	664	7942	75	0	254	22352	0	0	0	15350	7070
	PV+BT+Grid	13.63	0	0	11.39	0.0759	39796	27490	664	7942	75	0	254	22352	0	0	0	15350	7070
	PV+BT+DG+Grid	13.63	0	0	11.39	0.0759	39796	27490	664	7942	75	0	254	22352	0	0	0	15350	7070
	PV+BT+DG	**11.65**	**2.52**	**28**	**3.39**	**0.3761**	**90032**	**31350**	**3167**	**17146**	**84.3**	**0.0993**	**6389**	**19116**	**2023**	**6896**	**5524**	**0**	**0**
	PV+BT	24.8	0	109	12.47	0.8677	207685	83490	6703	34726	100	0.0999	25542	40679	0	8602	6863	0	0
Homer Pro	PV+Grid	13.5	0	0	12.7	0.0741	38933	27724	605	7976	75.1	0	46.9	22221	0	0	0	15432	7076
	PV+BT+Grid	13.8	0	0	11.1	0.0738	38814	27631	603.55	8008	75.1	0	391	22610	0	0	0	15458	7059
	PV+BT+DG+Grid	13.8	0	0	11.1	0.0738	38814	27631	603.55	8008	75.1	0	391	22610	0	0	0	15458	7059
	PV+BT+DG	**11.8**	**2.5**	**29**	**3.28**	**0.381**	**91126**	**31672**	**3209**	**17513**	**84.5**	**0.0978**	**6652**	**19383**	**2000**	**6822**	**5465**	**0**	**0**
	PV+BT	24.6	0	111	11.1	0.860	205899	82234	6674	34920	100	0.0979	25168	40365	0	8608	6868	0	0

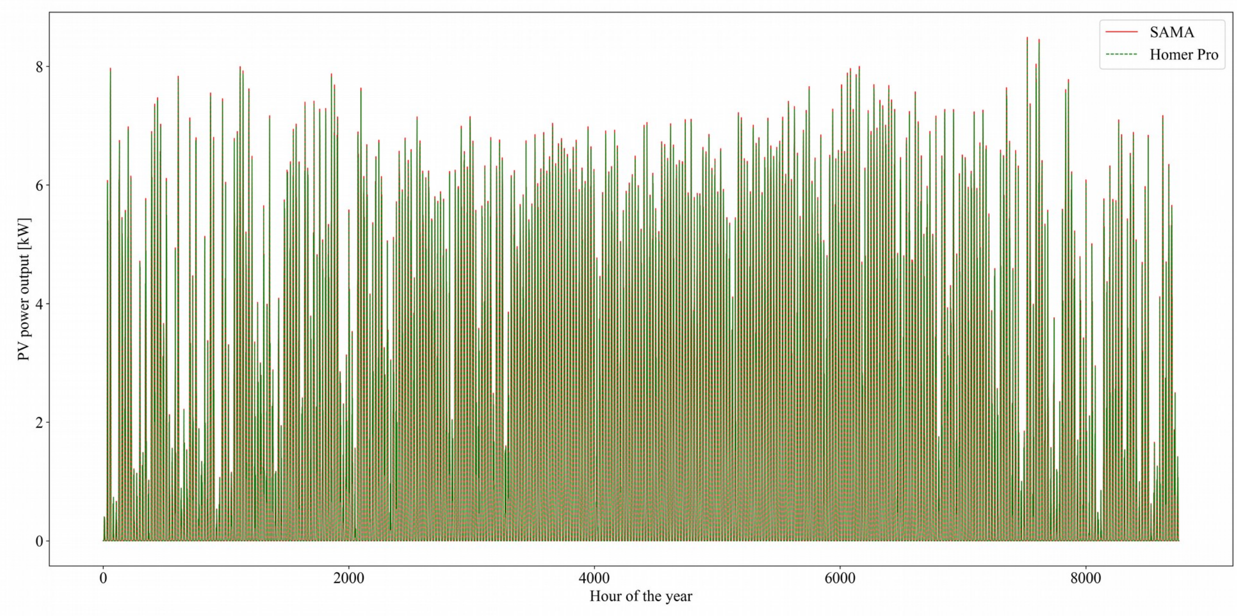

Fig.6a. Comparison of PV power output-SAMA vs Homer Pro

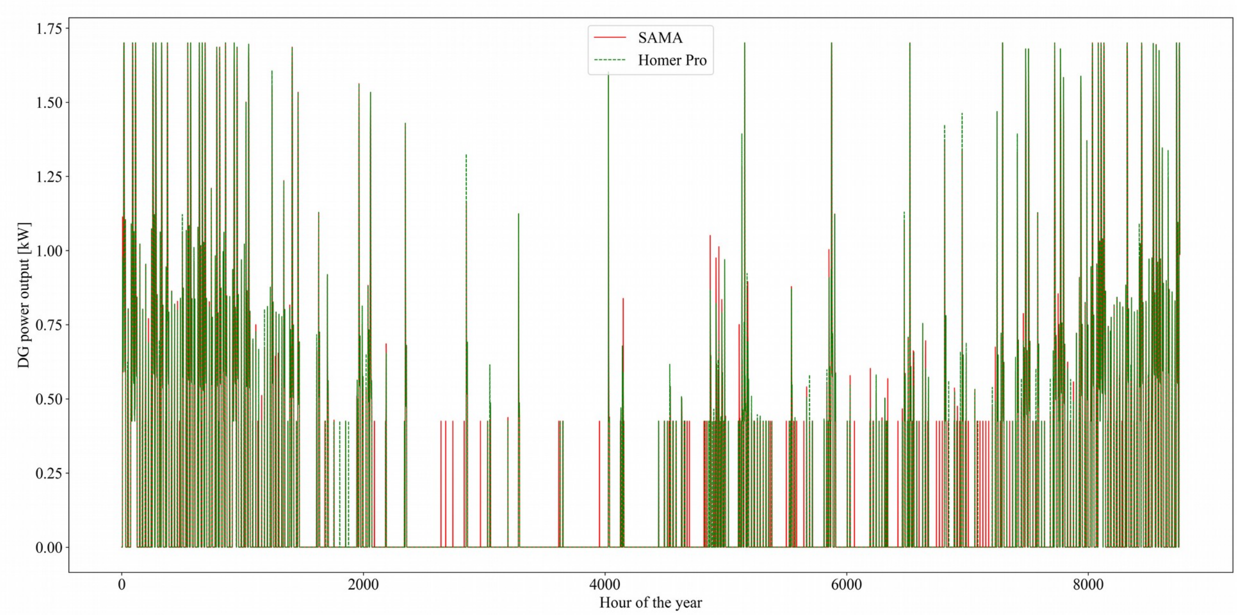

Fig.6b. Comparison of DG power output-SAMA vs Homer Pro

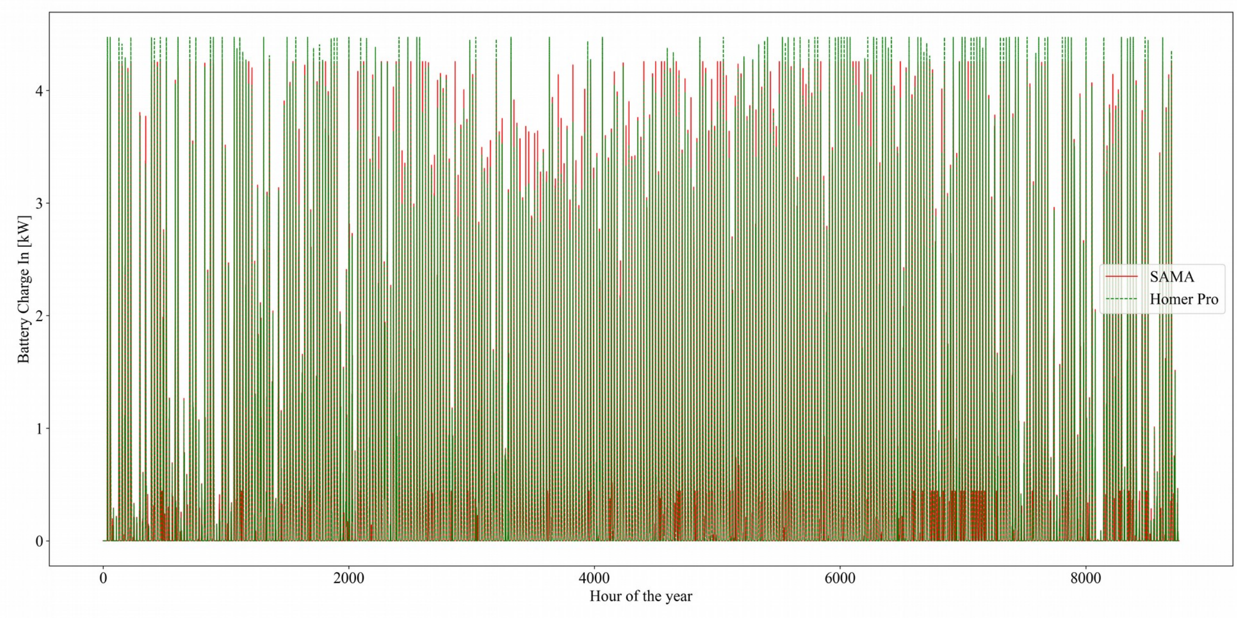

Fig.6c. Comparison of Battery Charge In-SAMA vs Homer Pro

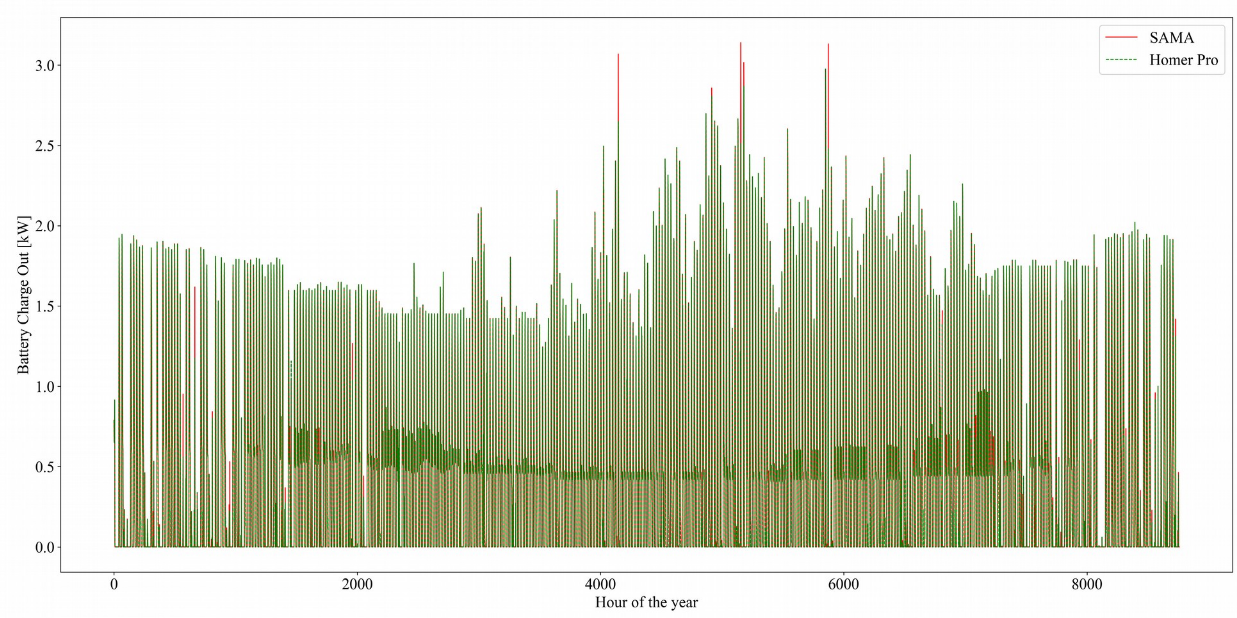

Fig.6d. Comparison of Battery Charge Out-SAMA vs Homer Pro

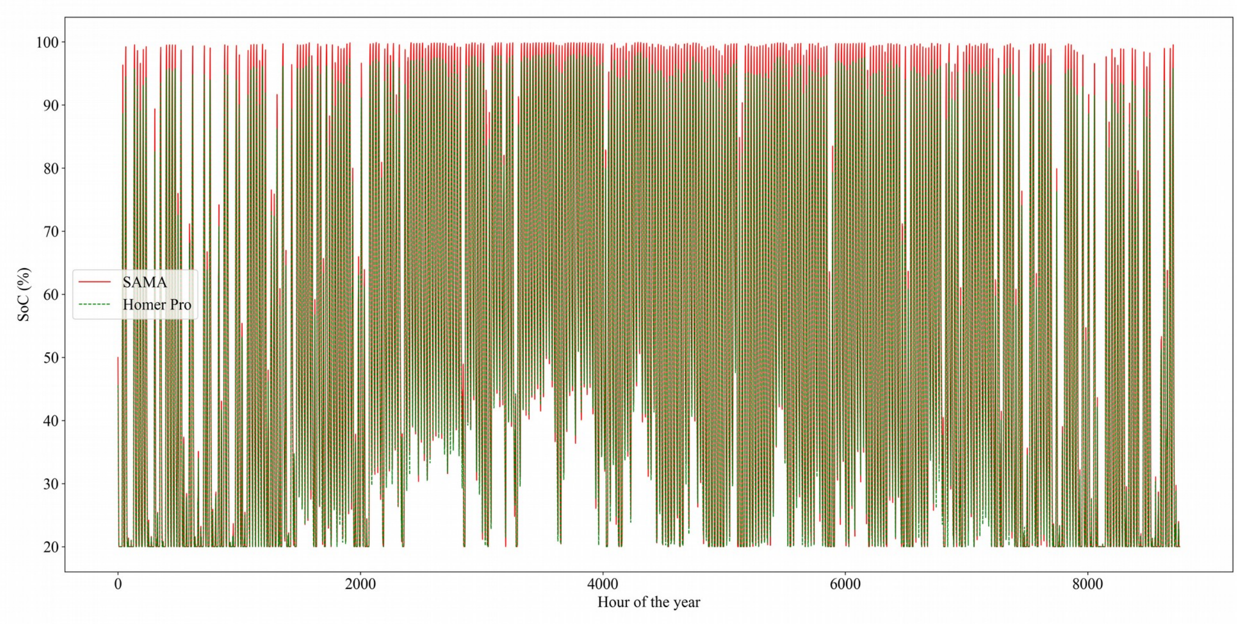

Fig.6e. Comparison of Battery SoC-SAMA vs Homer Pro

Fig.6. Hourly output comparison in SAMA and Homer Pro-Sacramento

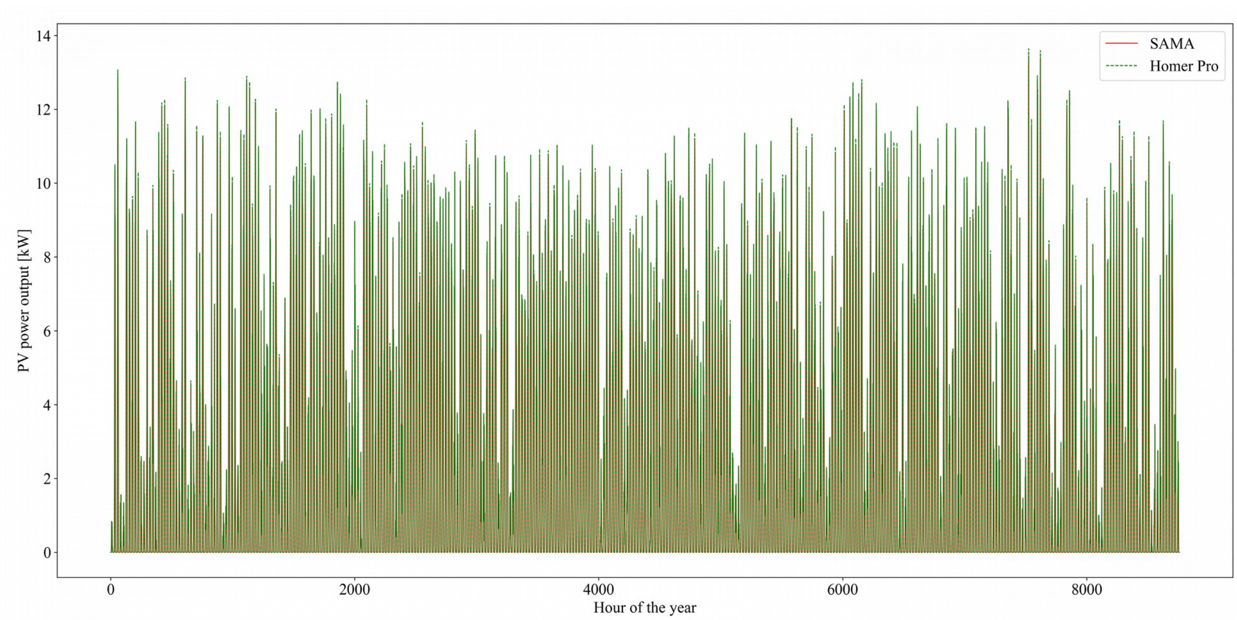

Fig.7a. Comparison of PV power output-SAMA vs Homer Pro

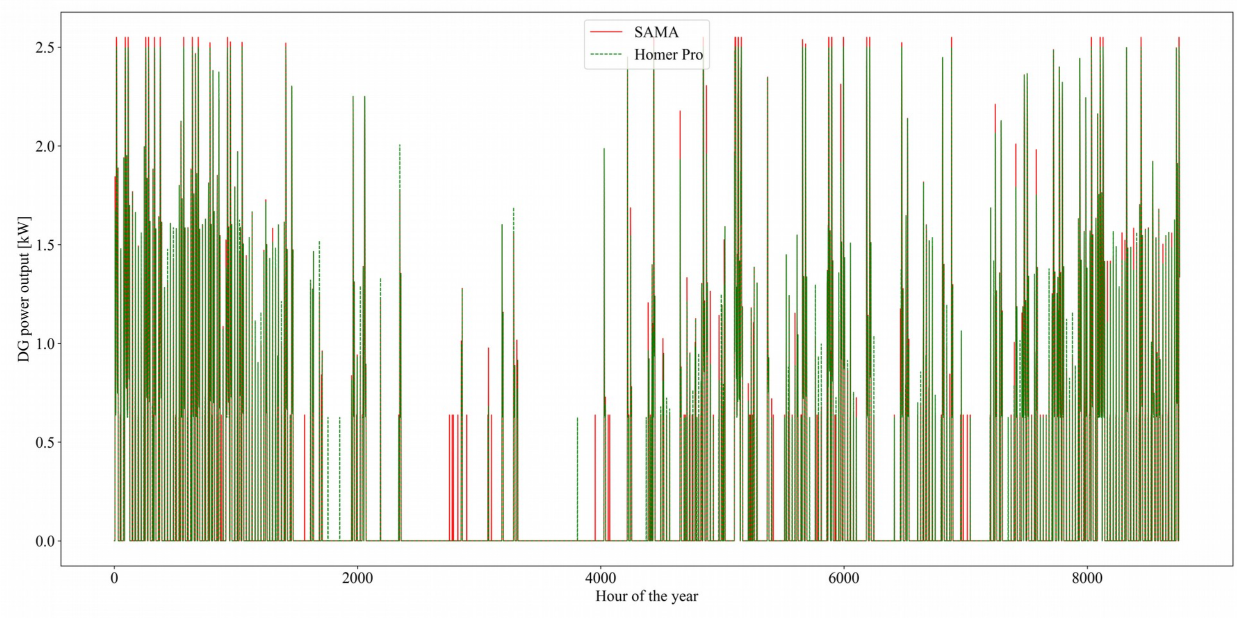

Fig.7b. Comparison of DG power output-SAMA vs Homer Pro

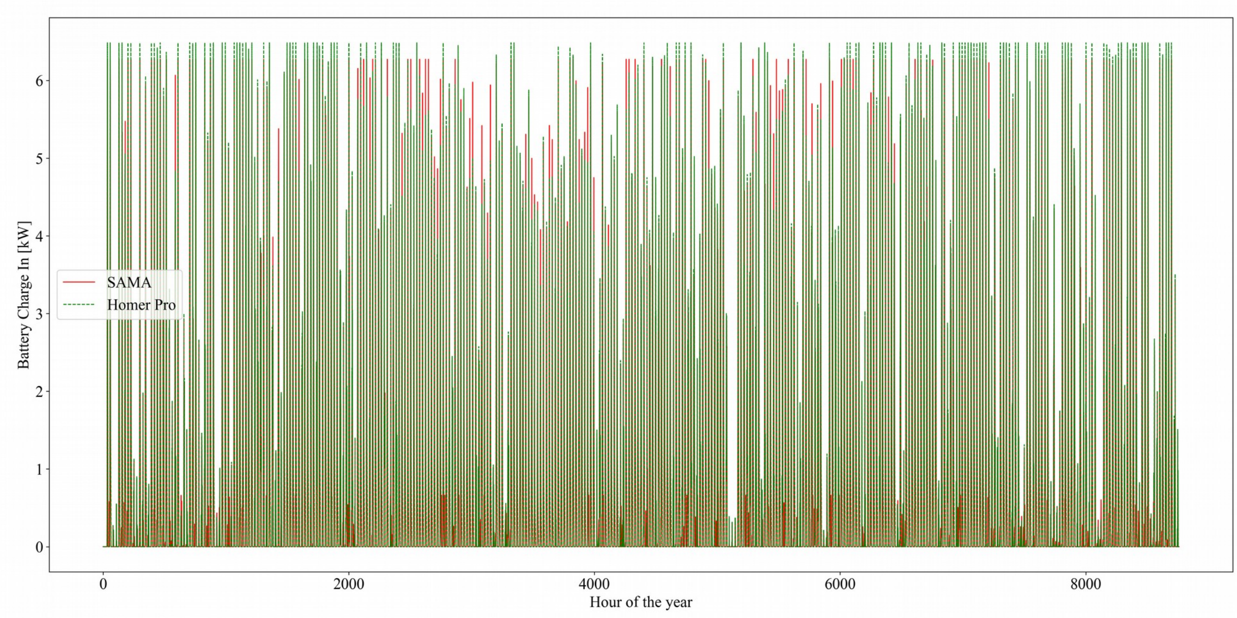

Fig.7c. Comparison of Battery Charge In-SAMA vs Homer Pro

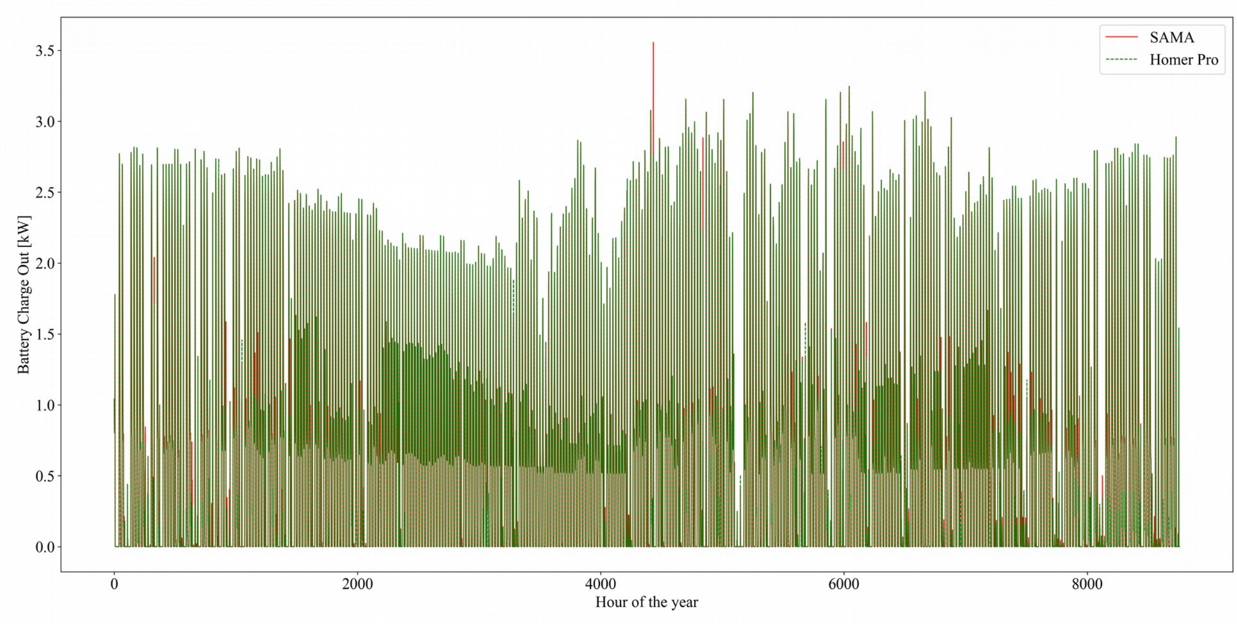

Fig.7d. Comparison of Battery Charge Out-SAMA vs Homer Pro

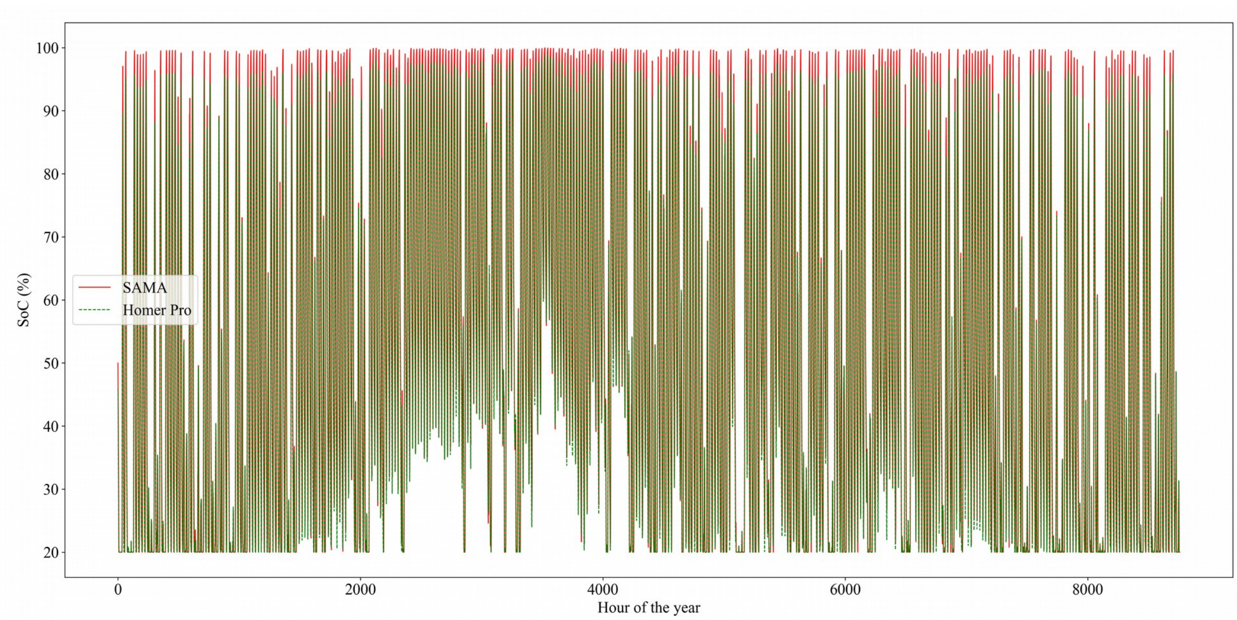

Fig.7e. Comparison of Battery SoC-SAMA vs Homer Pro.

Fig.7. Hourly output comparison in SAMA and Homer Pro-New Bern

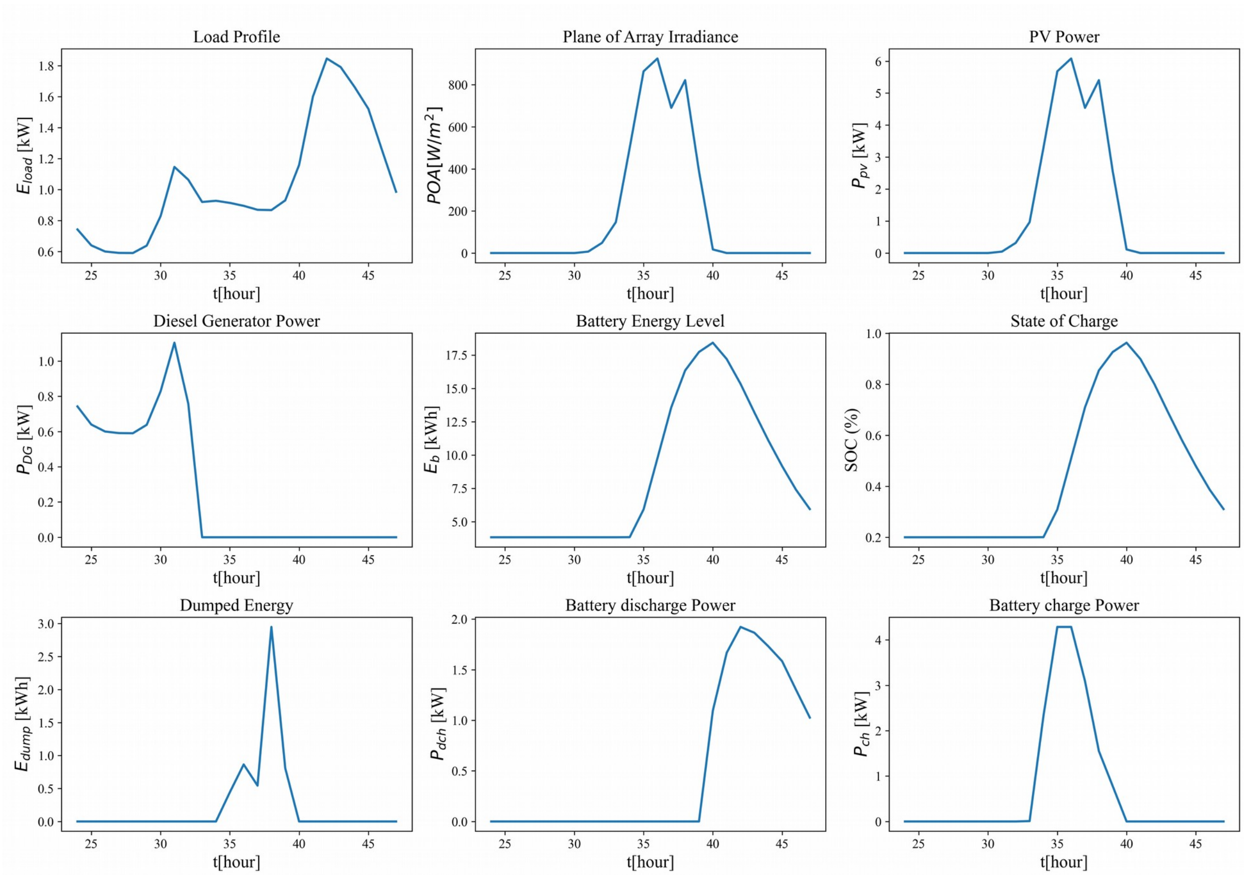

Fig.8a. Results of 1st day of year-Sacramento

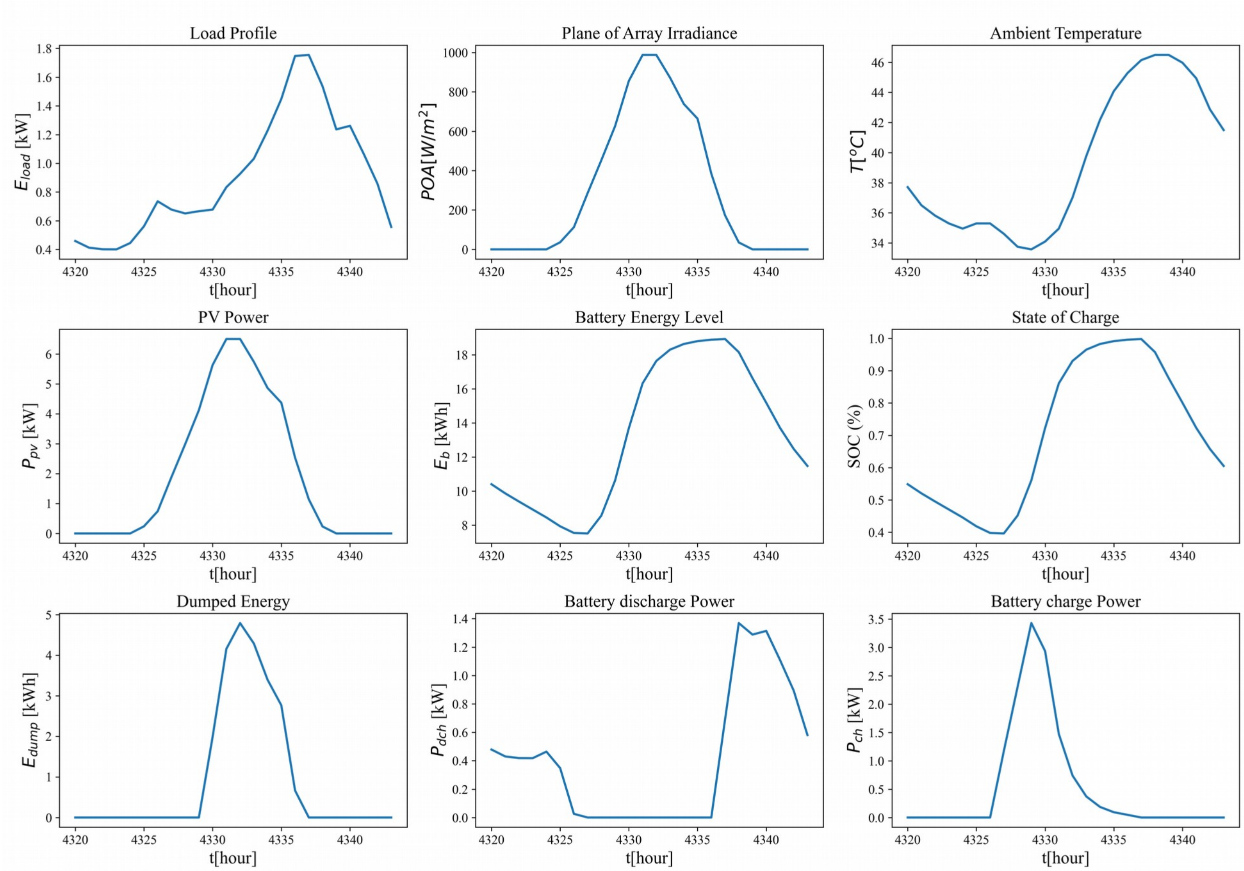

Fig.8b. Results of 180th day of year-Sacramento

Fig.8. Comparing SAMA's two specific day's outputs-Sacramento

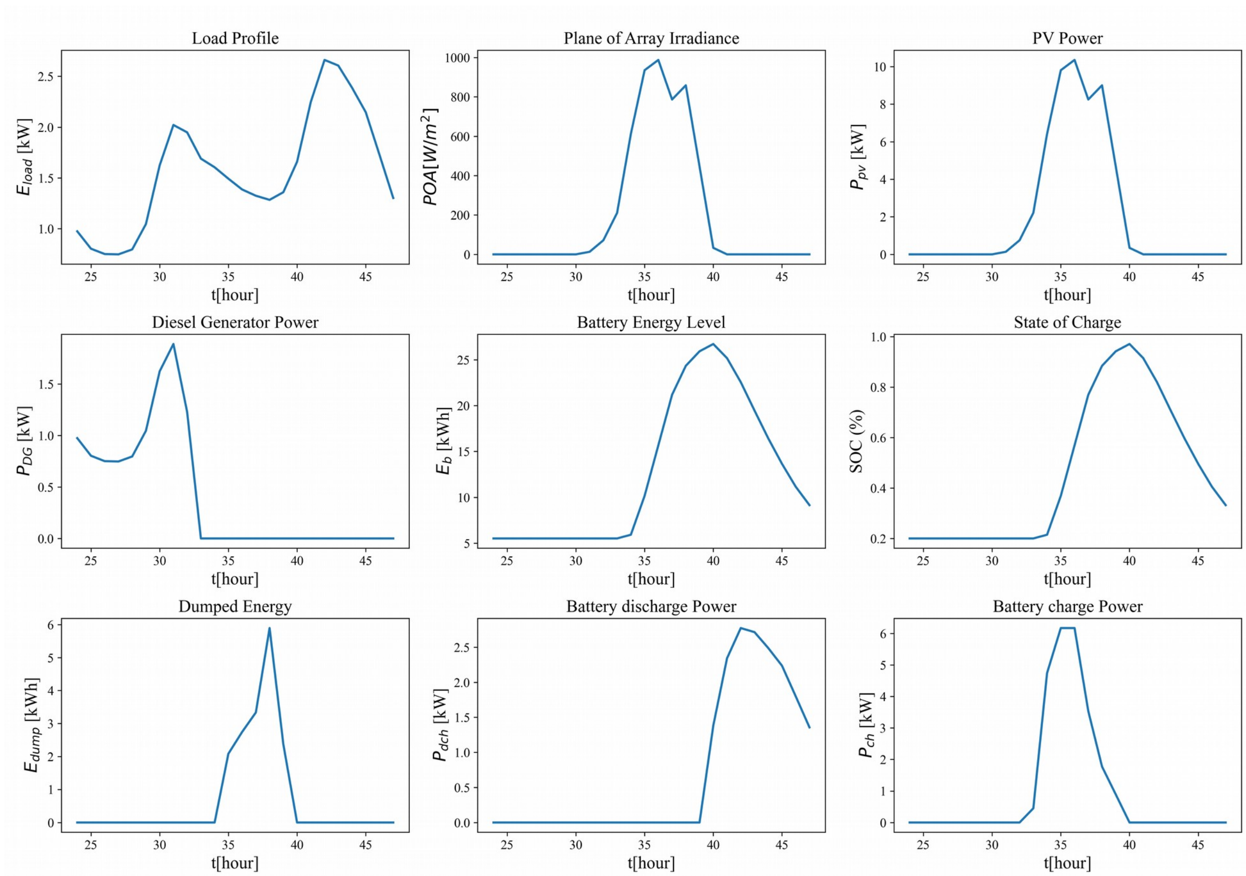

Fig.9a. Results of 1st day of year- New Bern

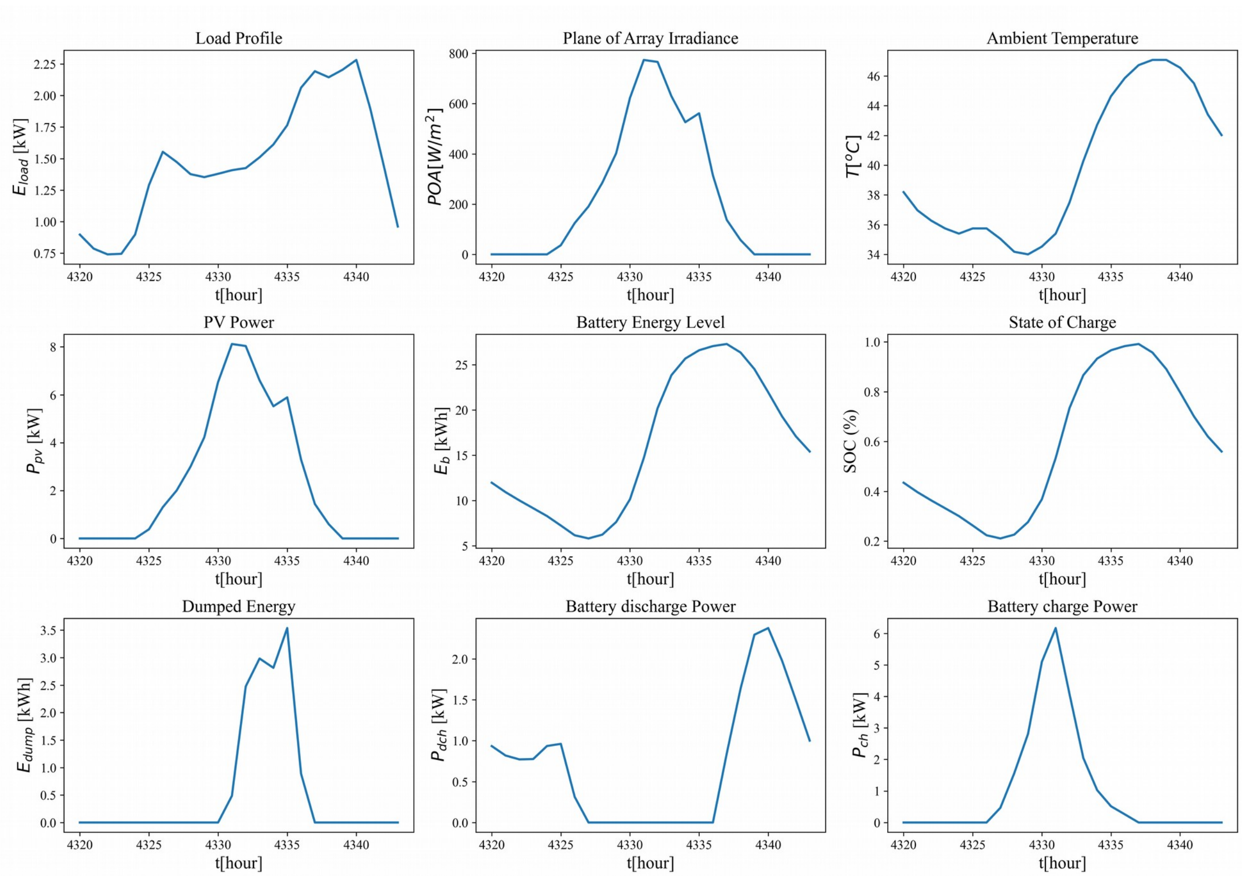

Fig.9b. Results of 180th day of year- New Bern

Fig.9. Comparing SAMA's two specific day's outputs -New Bern

6 References

[1] National Solar Radiation Database (NSRDB)., "Solar Resource Maps and Data." https://www.nrel.gov/gis/assets/images/solar-annual-ghi-2018-usa-scale-01.jpg (accessed Nov. 07, 2022).

[2] "Open Energy Data Initiative (OEDI)," *OpenEI*. https://data.openei.org/ (accessed Apr. 14, 2023).

[3] V. Ramasamy *et al.*, "US Solar Photovoltaic System and Energy Storage Cost Benchmarks, With Minimum Sustainable Price Analysis: Q1 2022," National Renewable Energy Lab. (NREL), Golden, CO (United States), 2022.

[4] "Homeowner's Guide to the Federal Tax Credit for Solar Photovoltaics | Department of Energy." https://www.energy.gov/eere/solar/homeowners-guide-federal-tax-credit-solar-photovoltaics (accessed Jan. 19, 2023).

[5] "iGen2200 Inverter Generator." https://westinghouseoutdoorpower.com/products/igen2200-inverter-generator (accessed Jan. 12, 2023).

[6] "Gasoline and Diesel Fuel Update." https://www.eia.gov/petroleum/gasdiesel/index.php (accessed Jan. 12, 2023).

[7] "U.S. No 2 Diesel Retail Prices (Dollars per Gallon)." https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EMD_EPD2D_PTE_NUS_DPG&f=M (accessed Jan. 16, 2023).

[8] A. L. Bukar, C. W. Tan, L. K. Yiew, R. Ayop, and W.-S. Tan, "A rule-based energy management scheme for long-term optimal capacity planning of grid-independent microgrid optimized by multi-objective grasshopper optimization algorithm," *Energy Convers. Manag.*, vol. 221, p. 113161, Oct. 2020, doi: 10.1016/j.enconman.2020.113161.

[9] "KiloVault HLX+ Deep-Cycle Lithium Solar Batteries (LiFePO4) | altE." https://www.altestore.com/store/deep-cycle-batteries/lithium-batteries/kilovault-hlx-lithium-solar-battery-p41627/#KLV3600HLXPLUL (accessed Jan. 16, 2023).

[10] C. Augustine and N. Blair, "Storage Futures Study: Storage Technology Modeling Input Data Report," National Renewable Energy Lab.(NREL), Golden, CO (United States), 2021.

[11] "Amazon.com : BougeRV 40A MPPT Solar Charge Controller, w/ Remote APP Control, Backlit LCD Display, Temperature Sensor, 12V/24V/36V/48V Battery Regulator, for Lithium, SLD, AGM, FLD, Gel Battery, Negative Ground : Patio, Lawn & Garden." https://www.amazon.com/BougeRV-Controller-Temperature-Regulator-Negative/dp/B09JZGBDPB (accessed Jan. 12, 2023).

[12] "US Discount Rate." https://ycharts.com/indicators/us_discount_rate#:~:text=US%20Discount%20Rate%20is%20at,long%20term%20average%20of%201.92%25. (accessed Jan. 12, 2023).

[13] "Projected U.S. inflation rate 2010-2027 | Statista." https://www.statista.com/statistics/244983/projected-inflation-rate-in-the-united-states/ (accessed Jan. 12, 2023).

[14] J. Hirvonen and K. Sirén, "A novel fully electrified solar heating system with a high renewable fraction - Optimal designs for a high latitude community," *Renew. Energy*, vol. 127, pp. 298–309, Nov. 2018, doi: 10.1016/j.renene.2018.04.028.

[15] C. P. Cameron, W. E. Boyson, and D. M. Riley, "Comparison of PV system performance-model predictions with measured PV system performance," in *2008 33rd IEEE*

Photovoltaic Specialists Conference, May 2008, pp. 1–6. doi: 10.1109/PVSC.2008.4922865.
[16] R. Dubey *et al.*, “Measurement of temperature coefficient of photovoltaic modules in field and comparison with laboratory measurements,” in *2015 IEEE 42nd Photovoltaic Specialist Conference (PVSC)*, Jun. 2015, pp. 1–5. doi: 10.1109/PVSC.2015.7355852.
[17] G. Blaesser and E. Rossi, “Extrapolation of outdoor measurements of PV array I–V characteristics to standard test conditions,” *Sol. Cells*, vol. 25, no. 2, pp. 91–96, Nov. 1988, doi: 10.1016/0379-6787(88)90014-2.
[18] V. Sun, A. Asanakham, T. Deethayat, and T. Kiatsiriroat, “Evaluation of nominal operating cell temperature (NOCT) of glazed photovoltaic thermal module,” *Case Stud. Therm. Eng.*, vol. 28, p. 101361, Dec. 2021, doi: 10.1016/j.csite.2021.101361.
[19] L. Dunn, M. Gostein, and K. Emery, “Comparison of pyranometers vs. PV reference cells for evaluation of PV array performance,” in *2012 38th IEEE Photovoltaic Specialists Conference*, Jun. 2012, pp. 002899–002904. doi: 10.1109/PVSC.2012.6318193.
[20] F. Prieto-Castrillo, N. Núñez, and M. Vázquez, “Warranty assessment of photovoltaic modules based on a degradation probabilistic model,” *Prog. Photovolt. Res. Appl.*, vol. 28, no. 12, pp. 1308–1321, Dec. 2020, doi: 10.1002/pip.3328.
[21] “Solar cell efficiency tables (Version 60) - Green - 2022 - Progress in Photovoltaics: Research and Applications - Wiley Online Library.” https://onlinelibrary.wiley.com/doi/full/10.1002/pip.3595 (accessed Jun. 04, 2023).
[22] E. Mulenga, A. Kabanshi, H. Mupeta, M. Ndiaye, E. Nyirenda, and K. Mulenga, “Techno-economic analysis of off-grid PV-Diesel power generation system for rural electrification: A case study of Chilubi district in Zambia,” *Renew. Energy*, vol. 203, pp. 601–611, Feb. 2023, doi: 10.1016/j.renene.2022.12.112.
[23] M. R. Elkadeem *et al.*, “Feasibility analysis and optimization of an energy-water-heat nexus supplied by an autonomous hybrid renewable power generation system: An empirical study on airport facilities,” *Desalination*, vol. 504, p. 114952, May 2021, doi: 10.1016/j.desal.2021.114952.
[24] N. Narayan, T. Papakosta, V. Vega-Garita, J. Popovic-Gerber, P. Bauer, and M. Zeman, “A simple methodology for estimating battery lifetimes in Solar Home System design,” in *2017 IEEE AFRICON*, Sep. 2017, pp. 1195–1201. doi: 10.1109/AFRCON.2017.8095652.
[25] A. F. Güven, N. Yörükeren, and M. M. Samy, “Design optimization of a stand-alone green energy system of university campus based on Jaya-Harmony Search and Ant Colony Optimization algorithms approaches,” *Energy*, vol. 253, p. 124089, Aug. 2022, doi: 10.1016/j.energy.2022.124089.
[26] G. A. Ghazi *et al.*, “African Vulture Optimization Algorithm-Based PI Controllers for Performance Enhancement of Hybrid Renewable-Energy Systems,” *Sustainability*, vol. 14, no. 13, Art. no. 13, Jan. 2022, doi: 10.3390/su14138172.
[27] S. Harb, M. Kedia, H. Zhang, and R. S. Balog, “Microinverter and string inverter grid-connected photovoltaic system — A comprehensive study,” in *2013 IEEE 39th Photovoltaic Specialists Conference (PVSC)*, Jun. 2013, pp. 2885–2890. doi: 10.1109/PVSC.2013.6745072.
[28] R. Kumar and H. K. Channi, “A PV-Biomass off-grid hybrid renewable energy system (HRES) for rural electrification: Design, optimization and techno-economic-environmental analysis,” *J. Clean. Prod.*, vol. 349, p. 131347, May 2022, doi: 10.1016/j.jclepro.2022.131347.

[29] "Rates," *Tucson Electric Power*. https://www.tep.com/rates/ (accessed Jun. 02, 2023).
[30] M. L. Nicolson, M. J. Fell, and G. M. Huebner, "Consumer demand for time of use electricity tariffs: A systematized review of the empirical evidence," *Renew. Sustain. Energy Rev.*, vol. 97, pp. 276–289, Dec. 2018, doi: 10.1016/j.rser.2018.08.040.
[31] "Electricity rates | Ontario Energy Board." https://www.oeb.ca/consumer-information-and-protection/electricity-rates (accessed Jun. 02, 2023).
[32] "Residential rates." https://www.smud.org/en/Rate-Information/Residential-rates (accessed Jun. 02, 2023).
[33] A. Seifi, M. H. Moradi, M. Abedini, and A. Jahangiri, "An optimal programming among renewable energy resources and storage devices for responsive load integration in residential applications using hybrid of grey wolf and shark smell algorithms," *J. Energy Storage*, vol. 27, p. 101126, Feb. 2020, doi: 10.1016/j.est.2019.101126.
[34] S. A. Sadat, B. Hoex, and J. M. Pearce, "A Review of the Effects of Haze on Solar Photovoltaic Performance," *Renew. Sustain. Energy Rev.*, vol. 167, p. 112796, Oct. 2022, doi: 10.1016/j.rser.2022.112796.
[35] A. H. Mondal and M. Denich, "Hybrid systems for decentralized power generation in Bangladesh," *Energy Sustain. Dev.*, vol. 14, no. 1, pp. 48–55, Mar. 2010, doi: 10.1016/j.esd.2010.01.001.
[36] A. Maleki and F. Pourfayaz, "Optimal sizing of autonomous hybrid photovoltaic/wind/battery power system with LPSP technology by using evolutionary algorithms," *Sol. Energy*, vol. 115, pp. 471–483, May 2015, doi: 10.1016/j.solener.2015.03.004.
[37] H. Lan, S. Wen, Y.-Y. Hong, D. C. Yu, and L. Zhang, "Optimal sizing of hybrid PV/diesel/battery in ship power system," *Appl. Energy*, vol. 158, pp. 26–34, Nov. 2015, doi: 10.1016/j.apenergy.2015.08.031.
[38] J. F. Manwell and J. G. McGowan, "Lead acid battery storage model for hybrid energy systems," *Sol. Energy*, vol. 50, no. 5, pp. 399–405, May 1993, doi: 10.1016/0038-092X(93)90060-2.
[39] G. P. Fenner, L. W. Stringini, C. A. S. Rangel, and L. N. Canha, "Comprehensive Model for Real Battery Simulation Responsive to Variable Load," *Energies*, vol. 14, no. 11, Art. no. 11, Jan. 2021, doi: 10.3390/en14113209.
[40] L. M. Rodrigues, C. Montez, R. Moraes, P. Portugal, and F. Vasques, "A Temperature-Dependent Battery Model for Wireless Sensor Networks," *Sensors*, vol. 17, no. 2, Art. no. 2, Feb. 2017, doi: 10.3390/s17020422.
[41] Y. Zhao, Y. Li, F. Zhou, Z. Zhou, and Y. Chen, "An iterative learning approach to identify fractional order KiBaM model," *IEEECAA J. Autom. Sin.*, vol. 4, no. 2, pp. 322–331, Apr. 2017, doi: 10.1109/JAS.2017.7510358.
[42] L. M. Rodrigues, N. L. Bitencourt, L. Rech, C. Montez, and R. Moraes, "An analytical model to estimate the state of charge and lifetime for batteries with energy harvesting capabilities," *Int. J. Energy Res.*, vol. 44, no. 7, pp. 5243–5258, 2020, doi: 10.1002/er.5269.
[43] E. A. Hyman, "Modeling and computerized characterization of lead-acid battery discharges. Battery Energy Storage Test (BEST) facility," *NASA STIRecon Tech. Rep. N*, vol. 83, p. 35290, Jan. 1983, Accessed: May 24, 2023. [Online]. Available: https://ui.adsabs.harvard.edu/abs/1983STIN...8335290H
[44] L. M. Rodrigues, C. Montez, F. Vasques, and P. Portugal, "Experimental validation of a battery model for low-power nodes in Wireless Sensor Networks," in *2016 IEEE World*

Conference on Factory Communication Systems (WFCS), May 2016, pp. 1–4. doi: 10.1109/WFCS.2016.7496519.
[45] J. F. Manwell, J. G. McGowan, U. Abdulwahid, and K. Wu, "Improvements to the Hybrid2 battery model," presented at the Windpower 2005 Conference, 2005.
[46] M. R. Jongerden and B. R. Haverkort, "Which battery model to use?," *IET Softw.*, vol. 3, no. 6, pp. 445–457, 2009.
[47] M. Jongerden and B. Haverkort, "Battery Aging and the Kinetic Battery Model," *Enschede Cent. Telemat. Inf. Technol. CTIT*, 2016.
[48] O. Yurur, C. H. Liu, and W. Moreno, "Modeling battery behavior on sensory operations for context-aware smartphone sensing," *Sensors*, vol. 15, no. 6, pp. 12323–12341, 2015.
[49] "How HOMER Calculates the Maximum Battery Charge Power." https://www.homerenergy.com/products/pro/docs/latest/how_homer_calculates_the_maximum_battery_charge_power.html (accessed Nov. 07, 2022).
[50] F. H. Jufri, D. R. Aryani, I. Garniwa, and B. Sudiarto, "Optimal Battery Energy Storage Dispatch Strategy for Small-Scale Isolated Hybrid Renewable Energy System with Different Load Profile Patterns," *Energies*, vol. 14, no. 11, Art. no. 11, Jan. 2021, doi: 10.3390/en14113139.
[51] M. Ashari, C. V. Nayar, and W. W. L. Keerthipala, "Optimum operation strategy and economic analysis of a photovoltaic-diesel-battery-mains hybrid uninterruptible power supply," *Renew. Energy*, vol. 22, no. 1, pp. 247–254, Jan. 2001, doi: 10.1016/S0960-1481(00)00013-6.
[52] T. Lambert, P. Gilman, and P. Lilienthal, "Micropower system modeling with HOMER," *Integr. Altern. Sources Energy*, vol. 1, no. 1, pp. 379–385, 2006.
[53] H. Suryoatmojo, A. A. Elbaset, and T. Hiyama, "Economic and reliability evaluation of wind-Diesel-Battery system for isolated island considering CO2 emission," *IEEJ Trans. Power Energy*, vol. 129, no. 8, pp. 1000–1008, 2009.
[54] A. Yahiaoui, F. Fodhil, K. Benmansour, M. Tadjine, and N. Cheggaga, "Grey wolf optimizer for optimal design of hybrid renewable energy system PV-Diesel Generator-Battery: Application to the case of Djanet city of Algeria," *Sol. Energy*, vol. 158, pp. 941–951, Dec. 2017, doi: 10.1016/j.solener.2017.10.040.
[55] C. D. Barley, "Modeling and optimization of dispatch strategies for remote hybrid power systems," Ph.D., Colorado State University, United States -- Colorado. Accessed: Nov. 07, 2022. [Online]. Available: https://www.proquest.com/docview/304245026/abstract/C2855FCA2530483EPQ/1
[56] C. Dennis Barley and C. Byron Winn, "Optimal dispatch strategy in remote hybrid power systems," *Sol. Energy*, vol. 58, no. 4, pp. 165–179, Oct. 1996, doi: 10.1016/S0038-092X(96)00087-4.
[57] H. Song *et al.*, "A novel hybrid energy system for hydrogen production and storage in a depleted oil reservoir," *Int. J. Hydrog. Energy*, vol. 46, no. 34, pp. 18020–18031, May 2021, doi: 10.1016/j.ijhydene.2020.09.081.
[58] "Salvage ValueBack ButtonSearch IconFilter Icon." https://www.homerenergy.com/products/pro/docs/3.11/salvage_value.html (accessed Jun. 05, 2023).
[59] D. P. Clarke, Y. M. Al-Abdeli, and G. Kothapalli, "Multi-objective optimisation of renewable hybrid energy systems with desalination," *Energy*, vol. 88, pp. 457–468, Aug. 2015, doi: 10.1016/j.energy.2015.05.065.

[60] A. Parlikar, C. N. Truong, A. Jossen, and H. Hesse, “The carbon footprint of island grids with lithium-ion battery systems: An analysis based on levelized emissions of energy supply,” *Renew. Sustain. Energy Rev.*, vol. 149, p. 111353, Oct. 2021, doi: 10.1016/j.rser.2021.111353.

[61] R. Ayop, N. M. Isa, and C. W. Tan, “Components sizing of photovoltaic stand-alone system based on loss of power supply probability,” *Renew. Sustain. Energy Rev.*, vol. 81, pp. 2731–2743, Jan. 2018, doi: 10.1016/j.rser.2017.06.079.

[62] S. Diaf, G. Notton, M. Belhamel, M. Haddadi, and A. Louche, “Design and techno-economical optimization for hybrid PV/wind system under various meteorological conditions,” *Appl. Energy*, vol. 85, no. 10, pp. 968–987, Oct. 2008, doi: 10.1016/j.apenergy.2008.02.012.

[63] “Welcome to New Bern, NC.” https://www.newbernnc.gov/departments/utilities/electric/electric_rates.php#outer-65 (accessed Jul. 19, 2023).

Appendix (SAMA output figures)-Off-grid PV-DG-BT

SAMA software output plots are illustrated in Fig. A1 to Fig. A2 for Sacramento-California and New Bern-North Carolina. Fig. A1 and Fig. A2 demonstrate the cash flow of the off-grid PV-DG-battery projects during their lifetimes (25 years) showing replacement times and costs, maintenance costs fuel costs and salvage value with revenues at top and costs at the down. These values are discounted over the lifetime of the project. The cash flow chart for both cities shows correct replacement of batteries and DG in the system, where batteries are replaced in 8th, 16th and 23th year, while DG is replaced in 14th year. The salvage value at the end of project calculated based on Eq. 44 is shown in 25th year. Comparing cash flow charts of both Sacramento case study and New Bern yields the fact that off-grid hybrid energy systems will cost more in New Bern compared to Sacramento. This is mostly due to the difference in geographies and climates of these cities. As shown with the total cost lines in both cities under current economics, maintaining a grid connection is clearly a more economic option.

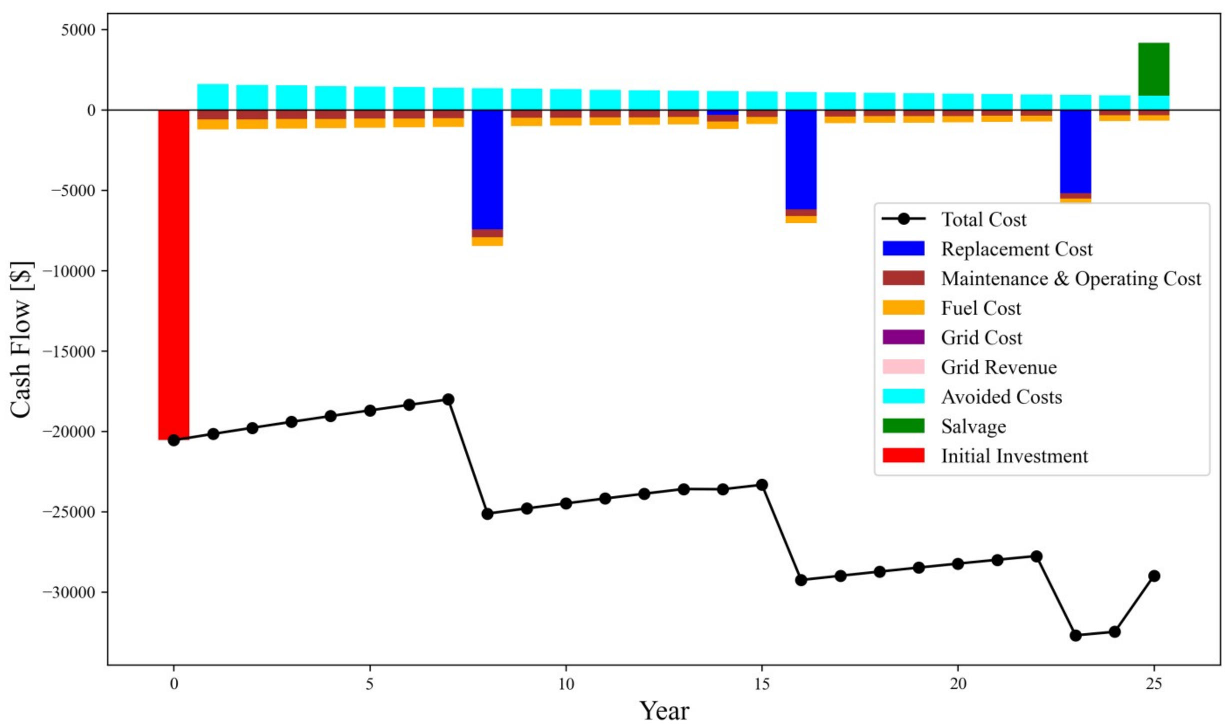

Fig.A1. Project cash flow-Sacramento

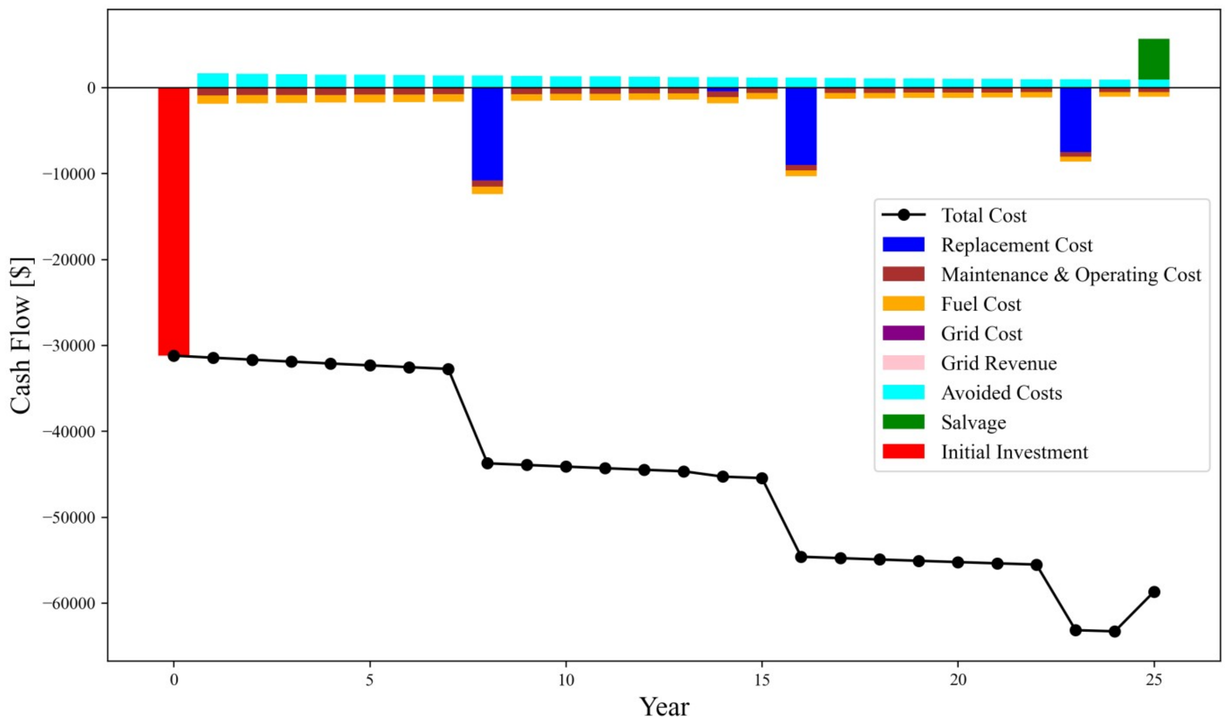

Fig.A2. Project cash flow-New Bern

Energy distributions of systems for both cities are plotted in Fig. A3 and Fig. A4. In both cases, PV modules from April to October will generate more power due to high level of irradiance. Irradiance levels are higher in Sacramento; hence PV output is higher compared to New Bern. In the times PV output is higher, for example, April to July, DG is operating less. Also, battery power is higher from June to October and lower during winter. The reason behind that is a higher solar irradiation level during summer compared to winter contributing higher PV output in summer and storing this energy in batteries. Fig. A5 and Fig. A6 show the behavior of the battery in system with a high level of charge during summer (due to higher irradiation and PV power output) and lower levels of charge during winter.

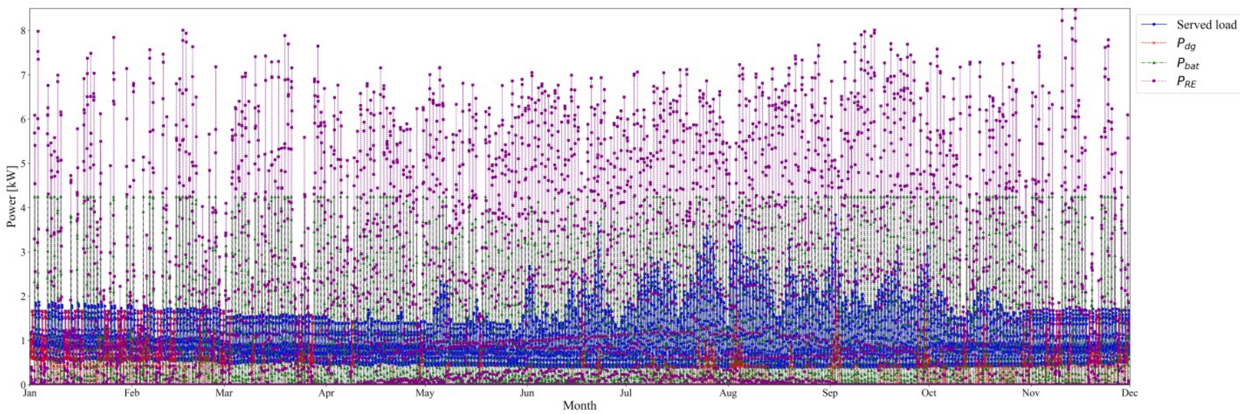

Fig.A3. Energy Distribution-Sacramento

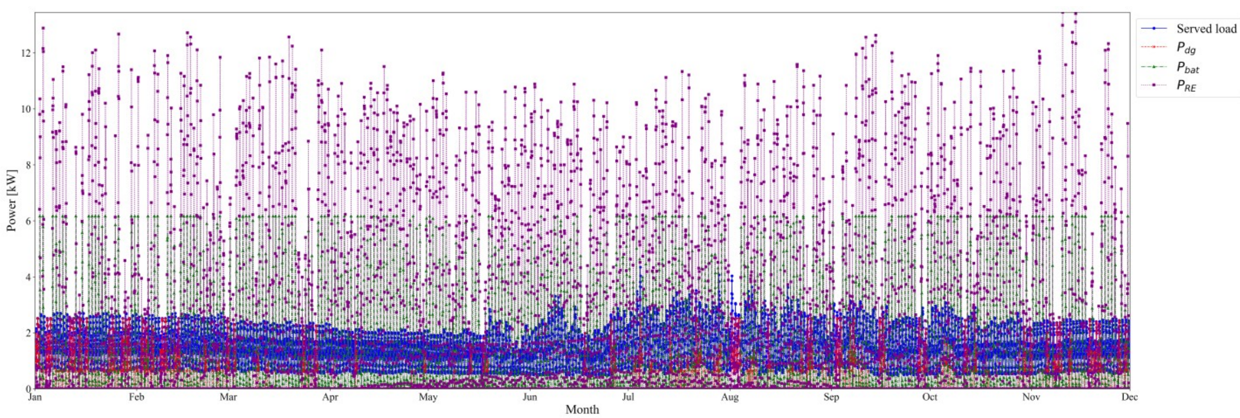

Fig.A4. Energy Distribution-New Bern

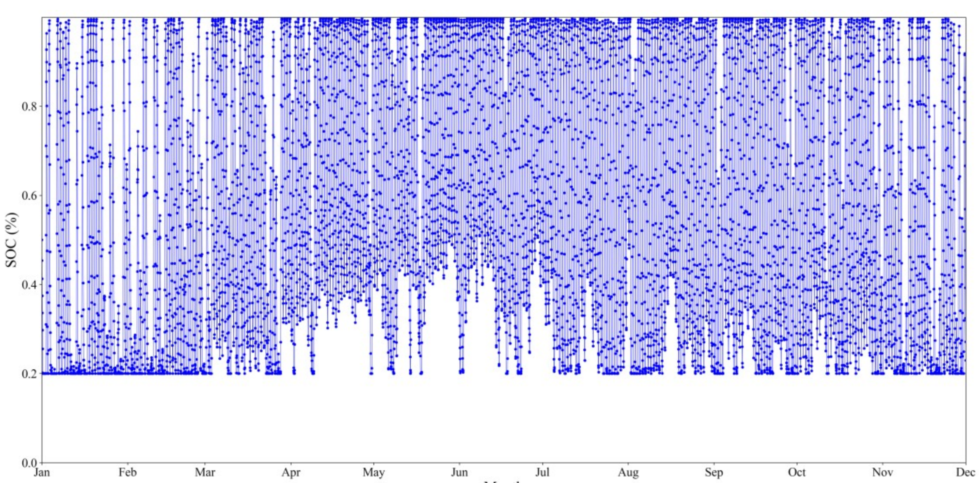

Fig.A5. Battery SoC-Sacramento.

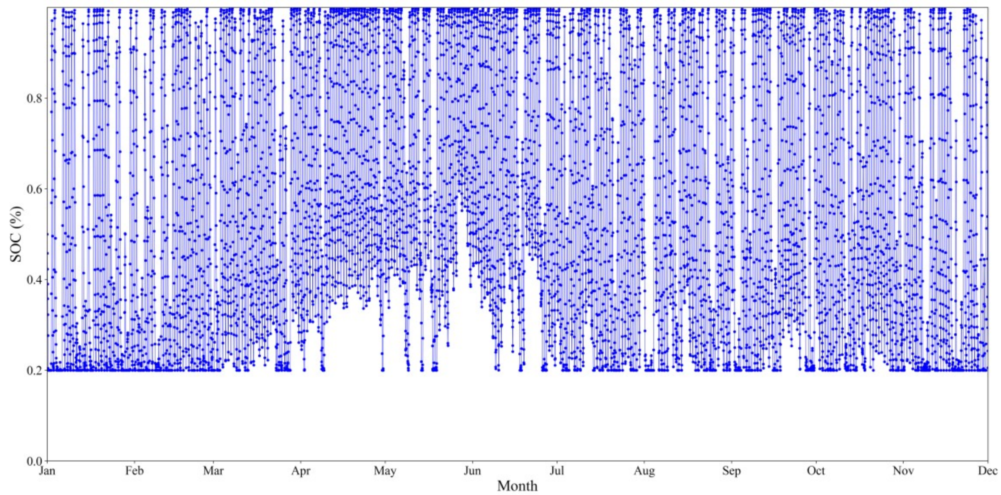

Fig.A6. Battery SoC-New Bern

SAMA also plots the daily, monthly and yearly average cost of energy system, shown in Fig.A7 and Fig. A8. For the purpose of grid-defection evaluations and researches, it is possible to use SAMA to compare relying only on the grid with the option of disconnect fully from the grid. Fig. A9 and Fig. A10 can thus be compared with Fig. A7 and Fig. A8. These figures provide useful insights into the daily, monthly and yearly costs of only relying on the grid (Fig.A9 and Fig. A10) and under investigation energy system (Fig.A7 and Fig. A8). Care should be taken, however, in comparing the heat maps across different situations as the scale is set for each individually. Monthly and yearly values can be compared numerically with the values on the right of each Figure. Overall, the results found that relying only on the grid in Sacramento will cost \$1,623 annually while the off-grid PV-DG-BT system will cost around two times more (\$3,133). As a result, SAMA's user can figure out that grid defection is not economically possible in Sacramento. Similarly, grid defection is not economically feasible in New Bern where an off-grid system will cost more than \$4,700 yearly in comparison with annual grid cost of \$1,656.60. The reason why off-grid solar hybrid energy system costs more in New Bern compared to Sacramento is that Sacramento is exhibiting higher solar irradiation, hence, smaller PV system for this city will be needed.

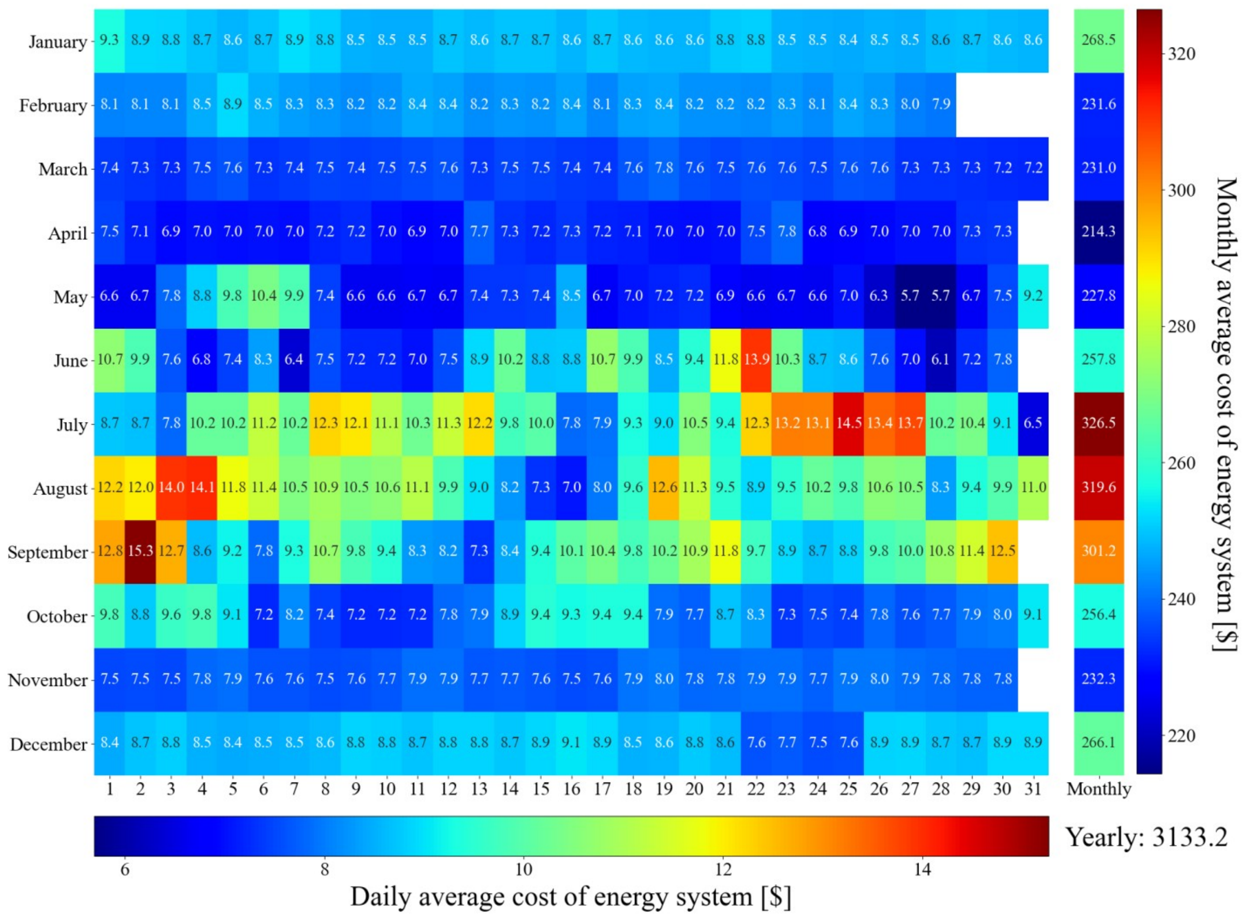

Fig.A7. Daily average cost of hybrid energy system-Sacramento

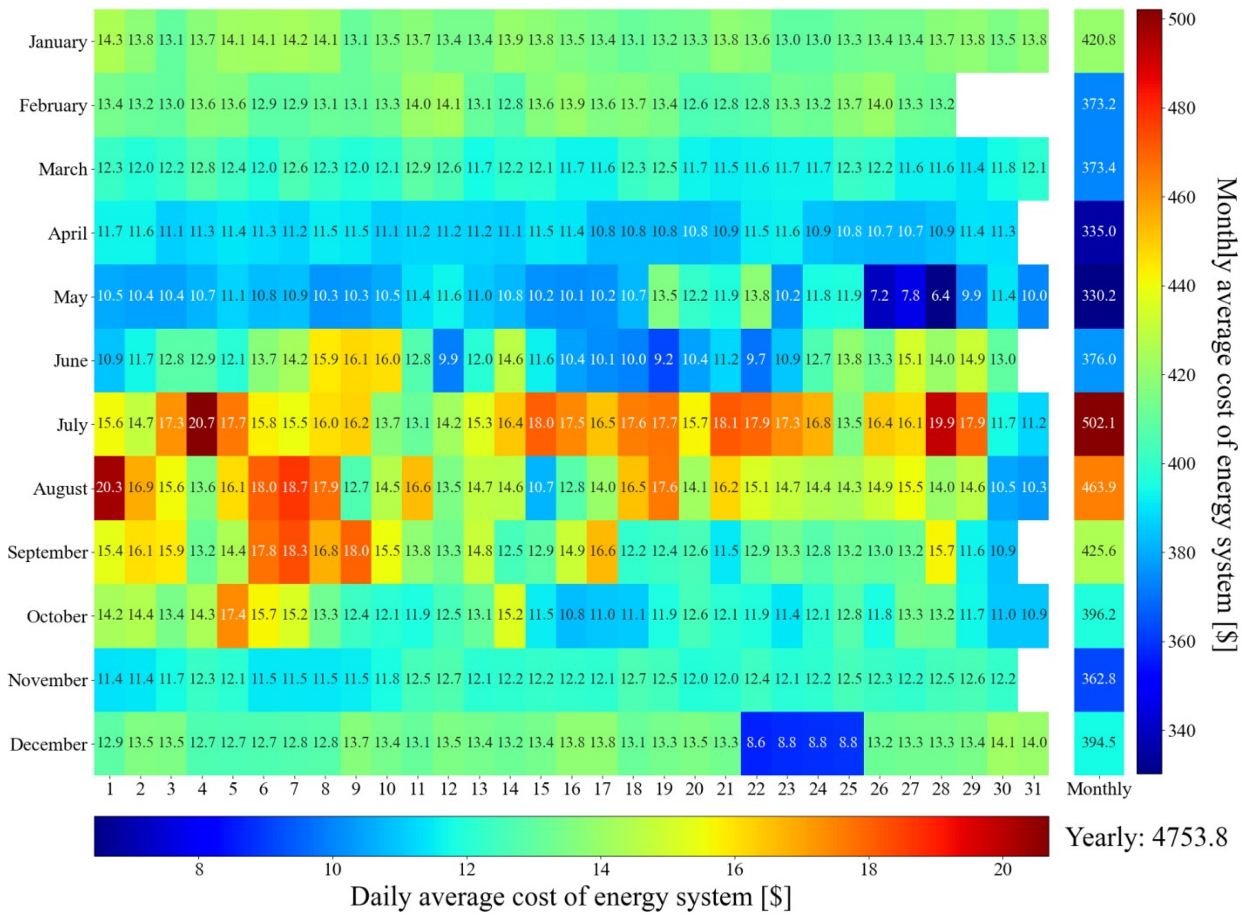

Fig.A8. Daily average cost of hybrid energy system-New Bern

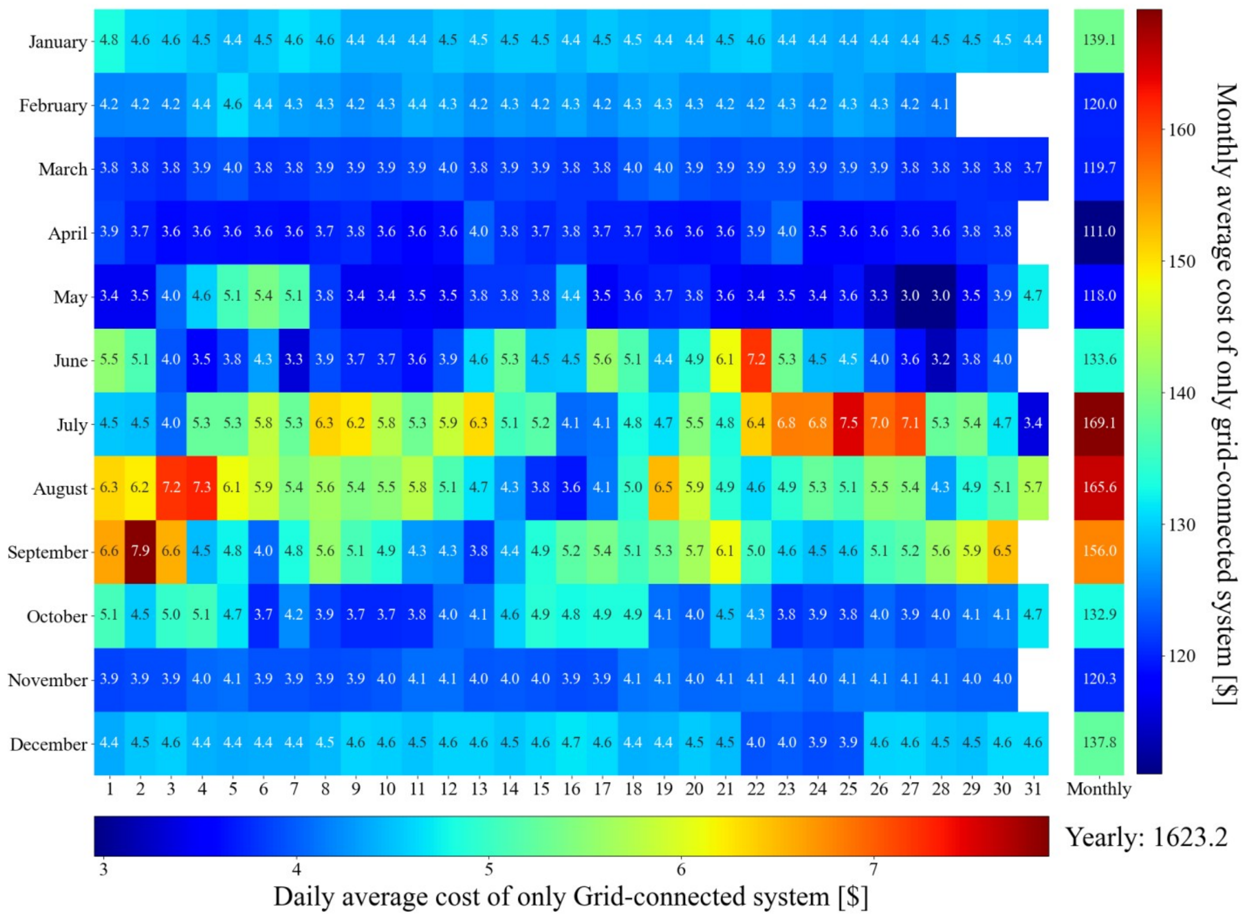

Fig.A9. Daily average cost of only grid connected system-Sacramento

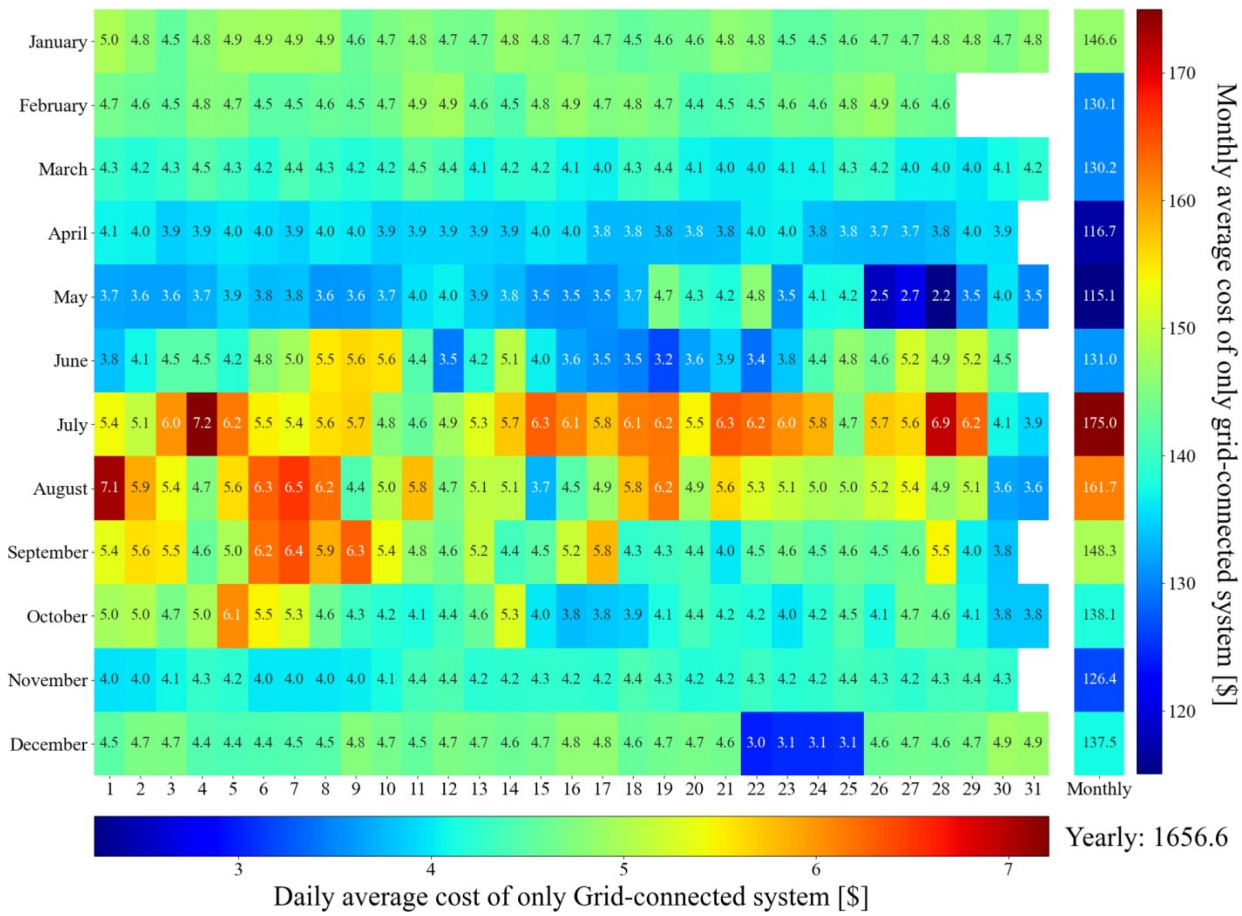

Fig.A10. Daily average cost of only grid connected system-New Bern

On the other hand, if the hybrid energy system is connected to grid where electricity shortage can be bought and excess electricity can be sold, PV energy system will be more profitable in both cases. The results for grid connected energy system by SAMA are plotted in Fig. A11 and Fig. A12. As it is previously shown in Table 3 and Table 4, if DG and BT for the grid connected system are chosen, the optimizer is not choosing any capacity for them as it can provide electricity with lower prices compared to cost of DG and BT. Another SAMA's output for grid analyses is illustrated in Fig.A13 for Sacramento and Fig.A14 for New Bern, representing the hourly cost of connecting to the grid. These figures are mainly dependent on the electricity utility structure of these cities and users can see the trend of grid electricity prices throughout the year.

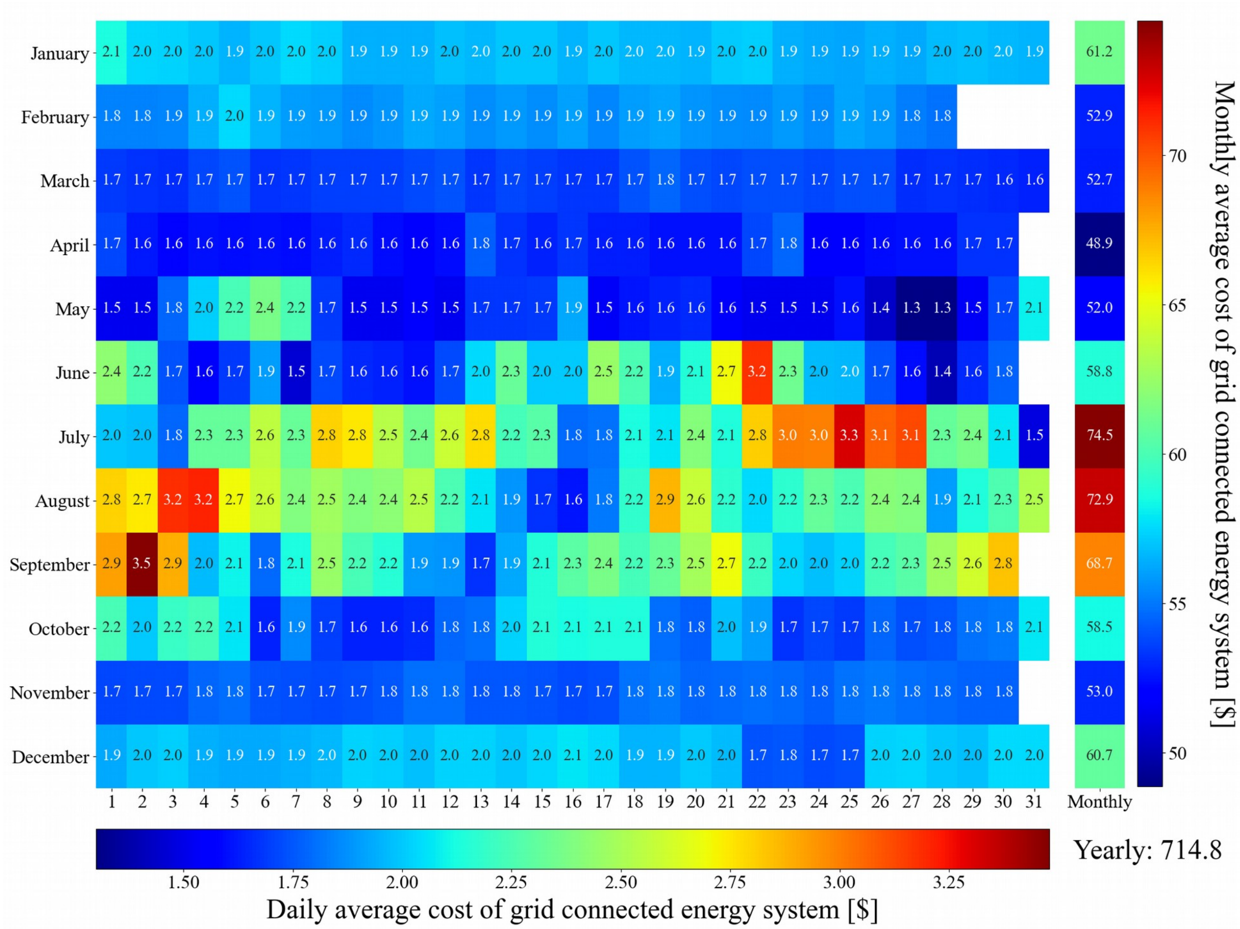

Fig.A11. Daily average cost of grid connected energy system-Sacramento

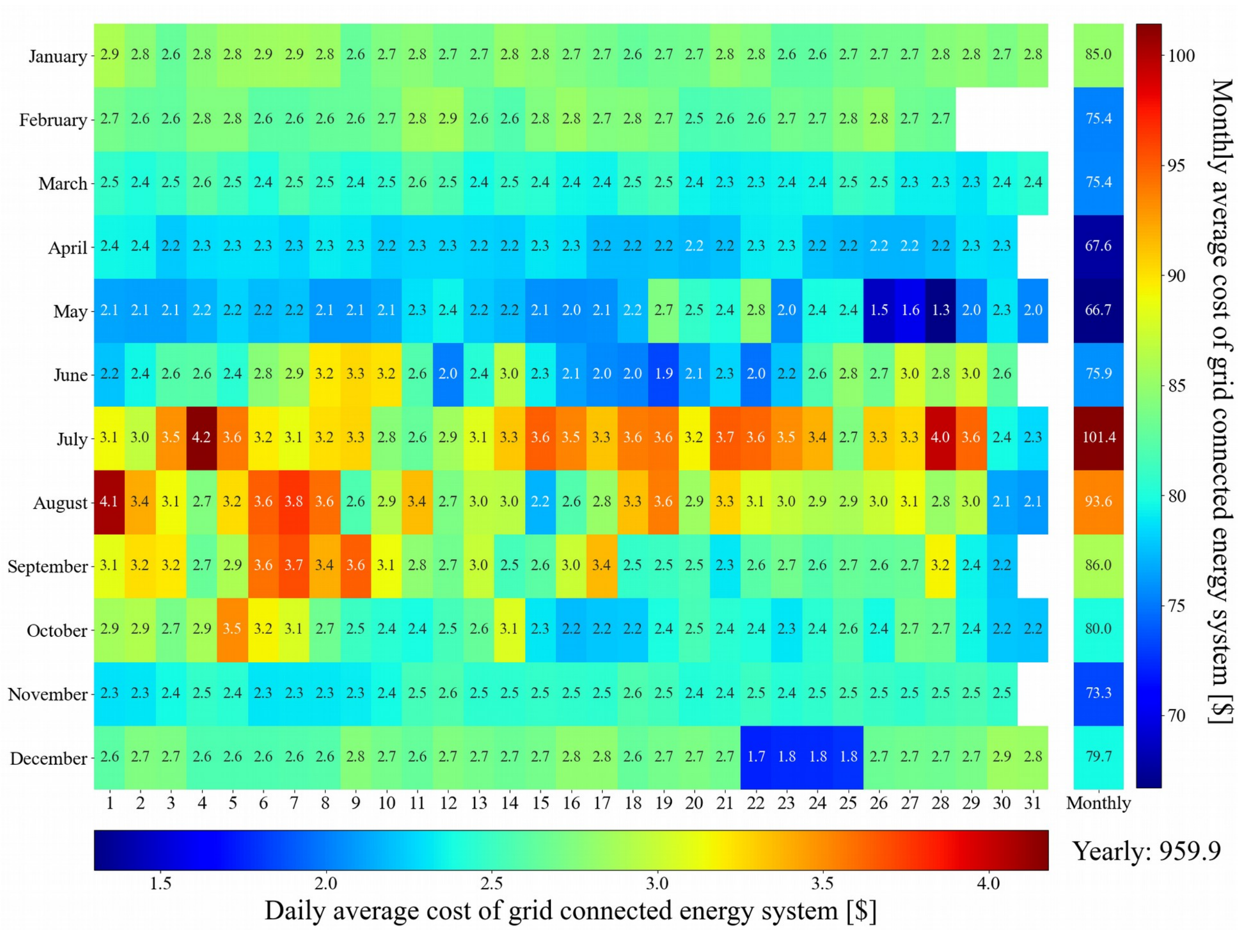

Fig.A12. Daily average cost of grid connected energy system-New Bern

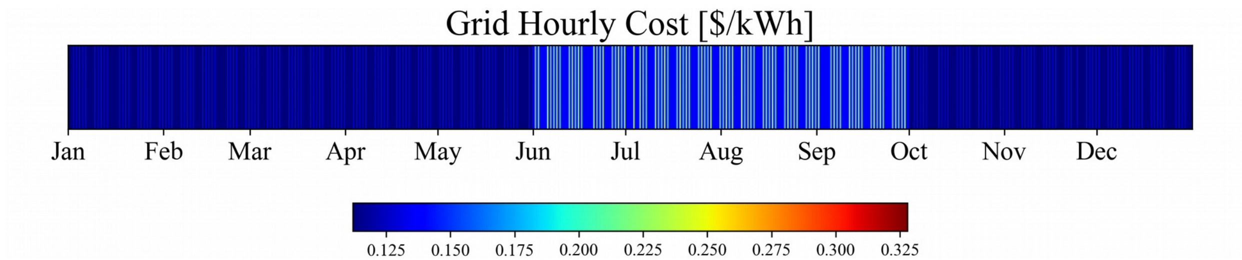

Fig.A13. Grid hourly cost per kWh heat map-Sacramento

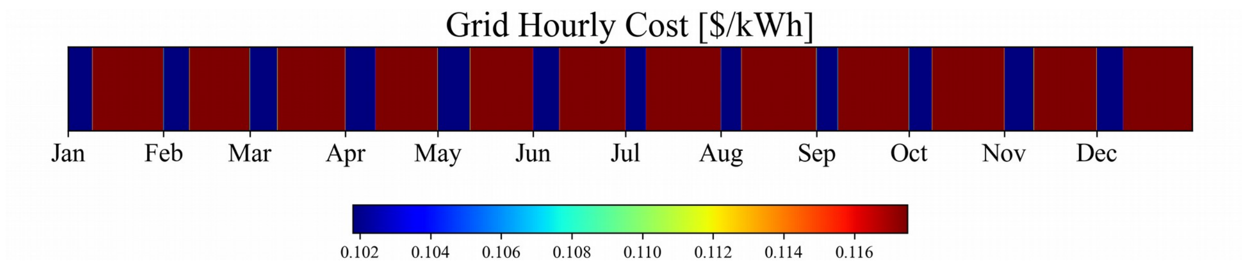

Fig.A14. Grid hourly cost per kWh heat map-New Bern