

Multi-Objective Optimization of Combined Heat and Power Economic Emission Dispatch in Multi-Energy Systems

SAMUEL ASOFORGHENA OGHOGBO^{1*}, ONYEGBADUE, IKENNA AUGUSTINE², GUIAWA MATHURINE³, IZILEIN FRED ABIEBHODE⁴

^{1, 2, 3, 4, 5} Department of Electrical and Electronics Engineering, Igbinedion University Okada, Edo State, Nigeria.

*Corresponding author: Samuel Asoforghena Oghogbo

Abstract- This paper presents a multi-objective energy management framework for residential multi-energy systems (MES) integrating photovoltaic (PV), wind, combined heat and power (CHP), battery energy storage system (BESS), thermal energy storage (TES), electric vehicle (EV), and grid resources. The research addresses the gap in coordinated economic–environmental optimization of highly coupled residential energy assets under renewable uncertainty and time-of-use pricing. A 24-h mathematical model minimizes energy expenditure and greenhouse-gas (GHG) emissions subject to electrical and thermal balance, generation, grid, storage, and EV operational constraints. NSGA-II and SPEA2 are implemented in Python/PyMOO and evaluated under three progressively complex scenarios. The proposed framework contributes an integrated scheduling architecture and scenario-based assessment of algorithmic performance. NSGA-II achieves –2.5592 ₦/day and 0.00040 kg/day in Scenario I, and –2.68698 ₦/day and 0.000296 kg/day in Scenario II, outperforming SPEA2 on both reported objectives. In Scenario III, NSGA-II attains 75.93173 ₦/day, while SPEA2 achieves 141,584.79 kg/day emissions. Convergence results show rapid initial NSGA-II improvement followed by stabilization, whereas SPEA2 exhibits progressive, archive-based refinement of the final non-dominated solution set.

Keywords: Combined heat and power (CHP), multi-energy system (MES), energy management, renewable energy, battery energy storage, thermal energy storage, electric vehicle, multi-objective optimization, NSGA-II, SPEA2.

I. INTRODUCTION

DERs are multi-energy systems that consist of power generation units like CHP, wind turbine, and PV. Recent surges in pollutant emissions, energy demands, and increase in fuel costs have drawn particular attention to DERs. Not only do DERs contribute to a

system by downsizing expenses, they are also more environment-friendly compared to centralized power systems. Of all the other DER constituents, CHPs are among the most beneficial technologies whose performances demand precise clarifications in this paper. A thermal power station's efficiency can be vastly improved by integrating Cogeneration or Combined Heat and Power (CHP) plants to the existing power system. CHP plants can produce power using a variety of fuels and also have the ability to recover and reuse the heat, which would have been generally wasted during power generation. The overall efficiency of the energy conversion process can be increased from 60% to a significant 80% by utilizing a CHP plant to produce power and heat simultaneously [1], [2]. The nucleus of CHP's utility is in its potential of generating both power and heat simultaneously. Accordingly, the system's entire energy efficiency is improved by using the heat waste to satisfy heating demands. There are two common operating modes for the CHP: Following Electric Load (FEL) and Following Thermal Load (FTL) [3]. At any time, any of both modes can be chosen based on Primary energy consumption, operating cost and carbon dioxide emission. The increased focus on sustainability has led many countries to integrate CHP units into their existing power system. This process will result in saving precious resources while also leading to pocket-friendly operations of a power system [4]. Electricity production by fossil fuels results in the emission of Sulphur dioxide (SO₂), Nitrogen oxides (NO_x) and other greenhouse gases [5]. These gases pollute the air, produce acid rain, and are also the major contributors to global warming. Also, they cause various health-related issues in human beings, harmful effects on biodiversity, and ecosystem.

Reduction of air pollution and their harmful effects are the key reasons all electric companies are compelled to minimize their emissions [6]. Furthermore, smart MES is an integrated system combining different networks such as gas, electricity, and heat to utilize their collective performances in terms of technical, economic, and environmental aspects [7]. Besides presenting optimization capability at both operational and planning stages, it is also possible to convert higher-priced energy into lower-priced energy depending on the consumer's preference [8]. Essentially, MESs have genuinely vast benefits that range from providing operational flexibility and sustainability of energy utilization, to enhancing reliability and resilience. Combined heating and power (CHP) and combined cooling, heat and power (CCHP) systems, heat pumps (HPs), boilers, refrigerators, thermal and electricity storage systems, power-to-gas (P2G) converter units are the main components of MES [9,10], which makes it difficult to model and operate this sophisticated architecture. As a solution, the concept of energy hub can be introduced as an important tool for MES modelling capable of not only conditioning and storing but converting multiple carriers, is presented [11].

Besides, integrating renewable energy resources such as photovoltaic (PV) and wind presents good opportunities in system operation of EH and has gained increasing global interest [12]. In addition, electric vehicles (EVs) have been represented as an attractive solution so as to increase flexibility and provide fast responding, economic and environment-friendly energy network. As an outcome, courtesy of the smart grid paradigm, the aforementioned circumstances are drawing attention to operating an MES structure enriched with renewable-based generation units and EVs. This paper therefore aims at presenting optimal MES management strategies, not only to mitigate the negative impacts of PV and wind turbine intermittencies but also to better coordinate hybrid CHP, grid network, electrical and thermal storage devices, EV, wind turbine and PV systems in residential buildings. MES mission is to schedule generation and storage devices while satisfying residential buildings' electrical and thermal demands. A multi-objective optimization algorithm has for this purpose, been applied on a typical residential building. The objective function is to minimize operating cost

and GHG emission through an NSGA II problem. The novelty of this work is attributed to: integrated MES structure consisting of CHP; thermal and electrical storage devices with different specifications; renewable-based generation units such as PV and wind along with residential EV. Every component above is taken into consideration towards achieving optimal operations in terms of minimizing total energy costs and Emission of GHG. Also, ToU pricing scheme is considered for electricity prices while the real gas prices are evaluated.

A scenario-based system modelling is considered for PV and wind power plants for investigating the impact of uncertainties on the system's operation.

Considering two types of energy storage devices—energy prosumer system (BESS and EV) and Thermal Energy Storage (TES).

II MATHEMATICAL FORMULATION

In this subsection, non-dominated sorting genetic algorithm-II (NSGA II)-based mathematical formulation is presented. Various forms of energy inputs, outputs and multilevel energy conversion process are considered. Under network constraints and uncertainties, each specific component is modelled by taking their operational limits into consideration in order to optimally manage MES. Most real-world problems involve simultaneous optimization of several objective functions. Generally, these functions are non-commensurable, often competing and conflicting objectives. Instead of one optimal solution, multi-objective optimization having such conflicting objective functions gives rise to a set of optimal solutions. The reason being that no solution can be considered to be better than any other with respect to all objectives. Optimal solutions in this category are known as pareto-optimal solutions. Generally, a multi-objective optimization problem consists of a number of objectives and several equality and inequality constraints. It simultaneously minimizes the m objective of the vector x in the feasible region. Its general mathematical model can be formulated as follows:

Minimize $f_i(x) \quad i = 1, \dots, N_{obj}$
(1)

Subject to $\begin{cases} g_k(x) = 0, k = 1, \dots, K \\ h_l(x) \leq 0, l = 1, \dots, L \end{cases}$
(2)

Where f_i is the i^{th} objective function, x is a decision vector that represents a solution.

Objective Functions: The objective functions of the proposed *MES* are energy cost and emissions which should be minimized.

Energy Cost: The end-users' net energy cost (C_T) comprises actual cost of electrical energy exchanged by main grid; cost of natural gas consumed by *CHP* over the scheduling horizon (24 hours); degradation cost associated with every discharging cycle of electric vehicle, and battery energy storage system batteries. The total cost can be formulated as follows:

$$C_T = \sum_{t=1}^{24} \left\{ \begin{aligned} &P_{grid,im}(t) \times TOU(t) + F_{CHP}(t) \times NG \\ &+ (P_{BESS}^{disch}(t) \times C_{BESS}^1 - P_{BESS}^{charg}(t) \times C_{BESS}^2) \\ &+ (P_{EV}^{disch}(t) \times C_{EV}^1 - P_{EV}^{charg}(t) \times C_{EV}^2) + P_{PV}(t) \times C_{PV} + P_w(t) \times C_w \end{aligned} \right\} \quad (3)$$

Where $TOU(t)$, NG , C_{BESS}^1 , C_{EV}^1 , C_{BESS}^2 and C_{EV}^2 refer to market time-of-use tariff at hour t (Naira/ kWh), natural gas price and cost of batteries maintenance correspond with discharging and charging intervals of *BESS* and *EV* batteries respectively. $P_{PV}(t)$, $P_w(t)$, C_{PV} and C_w are generated power from the *PV* and wind in period t , whereas C_{PV} and C_w are the maintenance costs of *PV* and wind systems.

Emissions: The function E_T includes total emission levels of CO_2 , NO_x and SO_x from natural gas consumption and from the main grid electricity usage over the scheduling horizon (24 h). It can be presented in equation (4) as follows:

$$E_T = \sum_{t=1}^{24} \left\{ \begin{aligned} &P_{grid,im}(t) \cdot (\mu_e^{CO_2} + \mu_e^{NO_x} + \mu_e^{SO_x}) \\ &+ F_{CHP}(t) \cdot (\mu_f^{CO_2} + \mu_f^{NO_x} + \mu_f^{SO_x}) \end{aligned} \right\} \quad (4)$$

Where $\mu_e^{CO_2}$, $\mu_e^{NO_x}$, $\mu_e^{SO_x}$ represent emission-converting factors for CO_2 , NO_x and SO_x for natural gas consumed by upstream grid (kg / kWh), $\mu_f^{CO_2}$, $\mu_f^{NO_x}$, $\mu_f^{SO_x}$ are emission-converting factors for CO_2 , NO_x and SO_x for natural gas consumed by cogeneration unit P_{CHP} expressed in (kg / m^3).

Equality constraints

The constraint is a mathematical expression that imposes a limit or restriction on the variables of the problem. So, all the constraints and conditions of the considered system are presented in the following equations

1. Power Balance Equality Constraint

Power balance equality constraint of the *MES* (expressed by 5) balances power imported from outer energy network (grid), produced power from a *CHP* unit. Power generated from *PV* and wind units; and power discharged from *EV* and battery are expressed with the sum total power demand P_d in residential buildings or end-users. Therefore, power balance constraint of the *MES* should guarantee the balance between electric production and consumption of the end-users as shown in Equ.5.

$$P_{grid}(t) + P_{CHP}(t) + P_{pv}(t) + P_{wind}(t) + P_{BESS}(t) + P_{EV}(t) = D_{elec}(t) \quad (5)$$

Note that the positive values for $P_{grid}(t)$ are regarded as the power purchased from the grid and the negative values as the power sold to the grid.

2. Heat Balance Equality Constraint

The heat balance equality constraint of the *MES* (6) balances the heat produced by both *CHP* and heat storage units with the total heat demand H_d of residential buildings or end-users.

$$H_{CHP}(t) + (H_{in}(t) \eta_{in} - H_{dr}(t) / \eta_{dr}) = H_D(t). \quad (6)$$

Power grid Model:

The injected electricity power from the National grid network during the period t for scenario v and w is determined by the amount of gas/coal consumed by

the national grid, $P_{grid}(KW)$ and can be expressed as:

$$P_{v,w,t}^{elec} = P_{v,w,t}^{elec,H_{device}} + P_{v,w,t}^{elec,BESS}, \quad \forall v, \forall w, \forall t \quad (7)$$

Electricity purchased from the outer grid network ($P_{v,w,t}^{elec}$) can be directly used to meet the electricity demands of the heat storage device and battery energy storage system (BESS) units stated in Eq. (8) as $P_{v,w,t}^{elec,H_{device}}$ and $P_{v,w,t}^{elec,BESS}$ respectively.

Power grid constraint:

The limit of the amount imported/purchased electricity from the main grid.

$$0 \leq P_{Grid}(t) \leq P_{Grid}^{max}(t) \quad (8)$$

$P_{Grid}^{max}(t)$ is the maximum imported power from the grid in t and the limit of the amount of sold electricity to the main grid is:

$$0 \leq P_{Grid,sell}(t) \leq P_{Grid,sell}^{max}(t) \quad (9)$$

$P_{Grid}^{max}(t)$ is the maximum sold power to the grid in t .

It is clear that importing/selling electrical energy from/to the upstream main grid at the same time is impossible. Consequently, the following inequality constraints for grid should be met.

$$v_{im}(t) + v_{sell}(t) \leq 1 \quad (10)$$

Photovoltaic System model:

Recently, due to their clean nature, photovoltaic systems have become promising energy sources for residential end-users [15]. Prior to mounting a PV system at any location, modelling, simulation and analysis of solar PV generator is a vital phase. It helps in understanding the real behaviours and characteristics in real climatic conditions of that location. Fig.1 depicts ideal Photovoltaic cell.

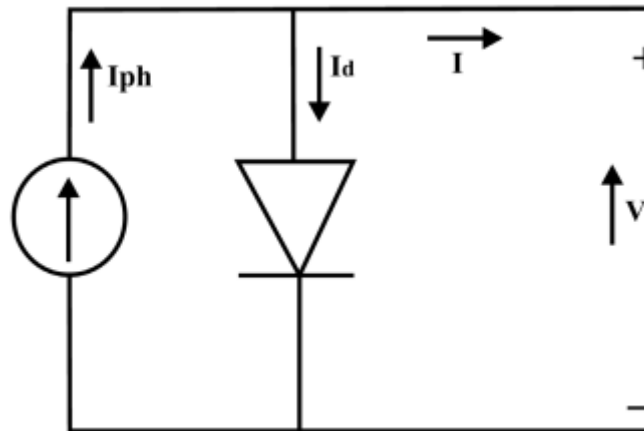


Fig. 1. Simplified equivalent circuit of PV panel

An ideal Photovoltaic cell consists of a single diode connected in parallel with a light generated current source, I_{ph} (Fig. 1), where, its output current, I , can be described as:

$$I = I_{ph} - I_s \left[\exp\left(\frac{V}{nV_T}\right) - 1 \right] \quad (11)$$

Where I_s = cell saturation of dark current, V_T = Thermal voltage = KT_c/q , k = Boltzmann's

constant = $1.38 \times 10^{-23} J/K$, T_c = cell's working temperature, q = electron charge, (1.6×10^{-19}), n = ideality factor equal to 1.1. In an ideal case, solar cell provides a very good approximation to photon-generated currents directly proportional to illumination intensity. There are some parameters not taken into consideration in ideal case models that actually affect the output of a PV device in real or practical conditions.

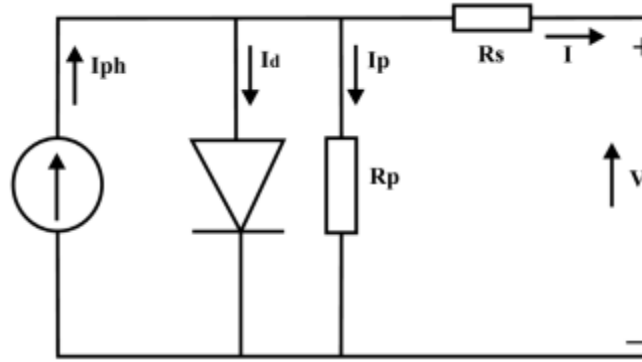


Fig.2. Equivalent circuit of real model for PV panel

A more realistic circuit model of solar PV cell is illustrated in Fig. 2. This is also identified as real single diode model with series resistance (R_s) and parallel resistance (R_p). Ideally R_s and R_p are ignored but in reality, it is not possible to overlook these resistances. The reason is that efficiency of the PV solar cell is affected by these parameters. R_s is series resistance in the current path and is considered as a loss by Joule effect. It is primarily due to metal grids, semiconductor materials, collecting bus and its connections. R_p is parallel resistance. It is associated with leakage of current due to the cell thickness, surface effects and also referred to as shunt resistance. The effect of R_s is prominent due to the multiplication of cells resistance in the PV module, compared to R_p . The effect of R_p is only conspicuous when large numbers of PV modules are considered in the solar photovoltaic system. The output power of photovoltaic cells depends on their efficiency and the amount of solar radiation received by the collector area. The solar radiation varies by the hour of the day while uncertainty in the forecasted solar photovoltaic (PV) generation results from the weather conditions including cloud coverage and temperature. The input of PV unit is supplied by the solar energy absorbed by the PV cells in the panel. The PV cells generate DC which charges battery; it is then sent to an inverter where it is converted from DC to AC suitable for end-user applications. Power output of the PV unit in the scheme is described in Eq. (12):

$$P_{v,w,t}^{pv} = P_{v,w,t}^{eleload,Demand} + P_{v,w,t}^{ele,BESS,Ch} + P_{v,w,t}^{ele,EVCh} \quad (12)$$

The hourly output power of PV unit ($P_{v,w,t}^{pv}$) is used to meet directly the electrical demands of the end-user

electric loads, end-user electric storage device and electric vehicle charging in the residential building as stated in Eq. (12): $P_{v,w,t}^{eleload,Demand}$, $P_{v,w,t}^{ele,BESS,Ch}$ and $P_{v,w,t}^{ele,EVCh}$ respectively. For the electric vehicle, this equality is guaranteed when $t \in T_{stay}$ (T_{stay} = period when EV stays at home). Otherwise, the EV power must be eliminated from the equation because in this research, it is considered that there is no charging process when the EV is away from home. The hourly output power produced by a PV module is given by

$$P_{pv} = A_{pv} \times H_{t(av)} \times \eta_{pv} \quad (13)$$

Where A_{pv} represents the area of PV module in m^2 , $H_{t(av)}$ (W / m^2) is the average global solar irradiation of the site and η_{pv} is the PV efficiency.

Constraints of the Photovoltaic system

The limit of the amount of PV generation is:

$$0 \leq P_{pv}(t) \leq P_{pv}^{max}(t). \quad (14)$$

$P_{pv}^{max}(t)$ is the maximum PV power allowed in t ;

and the output power produced from PV system [11]

$$P_{pv}(t) \leq A \times \eta \times SI(t) \quad (15)$$

Where A is the PV system area, η is the efficiency, and $SI(t)$ is solar irradiation in t .

Modelling of utility BESS charging/discharged power to the load

The development of energy storage technologies has created a potential role for the balancing of power produced from intermittent renewable energy sources.

In this research, the BESS is considered as the electrochemical battery. The BESS capacity as well as charging and discharging rates are important factors that should be taken into account in modelling. The BESS must be rated both in terms of power and energy capabilities. BESS modelling is essentially based on a balancing equation that defines its energy content every time sample t as a function of the amount of power either charges or discharges from the unit. The input power of utility storage device (VPP) is supplied from electricity purchased from the upstream main grid network and electricity produced from CHP using an integration multiplier $chp - hp_m$ that indicates if there is a connection between CHP and BESS as expressed in Eq. (16). Utility storage device (BESS) is capable of meeting electricity demands for lighting, other home appliances, and residential BESS denoted in Eq. (17).

$$\sum_n P_{n,v,w,t}^{BESS,input} = \sum_m P_{m,v,w,t}^{CHP_{ele},BESS, chp_bess_m} + P_{v,w,t}^{ele,BESS} \quad (16)$$

$$P_{v,w,t}^{BESS,input} = P_{v,w,t}^{BESS_{ele}end-user} + P_{v,w,t}^{end-user,elecload} \quad (17)$$

The net power output of battery in each time interval is given as follows:

$$P_{BESS} = P_{ch}(t) \cdot \eta_{ch} - \frac{P_{discharge}(t)}{\eta_{discharge}} \quad (18)$$

The charge and discharge rates of BESS in each interval t are bounded by maximum charge/discharge rate of the converter that connects BESS to *MES* as follow:

The electricity input of ($P_{v,w,t}^{BESS,input}$) is limited considering discharging power of utility (BESS) by certain upper bounds.

$$0 \leq P_{ESS,utility}^{dischg}(t) \leq P_{BESS,utility}^{dischg,max} \times Z(t) \cdot \eta_{dischg} \quad (19)$$

$\forall uti \in S_{BESS}, \quad t = 1, \dots, 24.$

The limit of allowed charging

$$0 \leq P_{BESS,utility}^{ch} \leq P_{BESS,utility}^{Ch,max} \times \frac{Y(t)}{\eta_{ch}} \quad (20)$$

For the fact that *BESS* cannot be charging and discharging simultaneously, the constraint of Eq. (21) should be met.

$$Z_{ch}(t) + Y_{disch}(t) \leq 1 \quad (21)$$

The battery State of Charge (*SOC*) and its minimum and maximum limitations are formulated as follows:

$$SOC(t) = SOC(t-1) + \frac{\tau(P_{ch}(t) \cdot \eta_{ch} - P_{disch}(t) / \eta_{disch})}{C_{BESS}} \quad (22)$$

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \quad (23)$$

τ and C_{BESS} are the respective the time resolution ($1h$) and battery capacity.

Modelling of wind turbine System:

The power production of a wind unit is dependent on the wind speed. The power output of the wind turbine is presented using a linear function once the wind speed is between the cut-in and rated wind speed limits. Power production is constant once the wind speed is above the rated value and below the cut-out limit. The Weibull probability distribution function (PDF), autocorrelation factors, and diurnal wind pattern simulate uncertainty in wind speed [12]. Wind turbine units' power output can be used to meet the electricity end-users' demands, end-users' electricity storage device and end-users' electric vehicle as described in Eq. (24).

$$P_{v,w,t}^{wind} = P_{v,w,t}^{eleload,Demand} + P_{v,w,t}^{ele,BESS,Ch} + P_{v,w,t}^{ele,EVCh} \quad (24)$$

The power curve of a wind turbine's mathematical model has been calculated and given by:

$$P_w = \begin{cases} 0 & V < V_{ci} \\ P_r \left(\frac{V^3 - V_{ci}^3}{V_r^3 - V_{ci}^3} \right) & V_r < V < V_{co} \\ P_r & V_r < V < V_{co} \\ 0 & V > V_{co} \end{cases} \quad (25)$$

$P_w(inW / m^2)$ is the output power generated by the wind turbine and P_r is the rated power (W). Also, V, V_{ci}, V_r, V_{co} are the instantaneous wind speed in

(m/s), cut-in wind speed in, rated speed in (m/s) and cut-out wind speed in (m/s) respectively.

The electrical power delivered by the turbine is calculated using:

$$P_{wind-out} = P_w \times A_w \times \eta_e \quad (26)$$

Where A_w is the total swept area of the wind turbine in m^2 , η_e is the electrical efficiency of the wind

generator and any other electrical components connected to the generator.

Modelling of CHP unit:

A comprehensive CHP model comprising three main components— power generator, turbine, and heat recovery unit— is proposed. Fig.3 depicts the configuration of a cogeneration unit in the proposed MES system. As can be seen in Fig.4, gas is fed into a CHP unit to generate electricity, then the HRU uses the heat waste to meet end-users' heating demands.

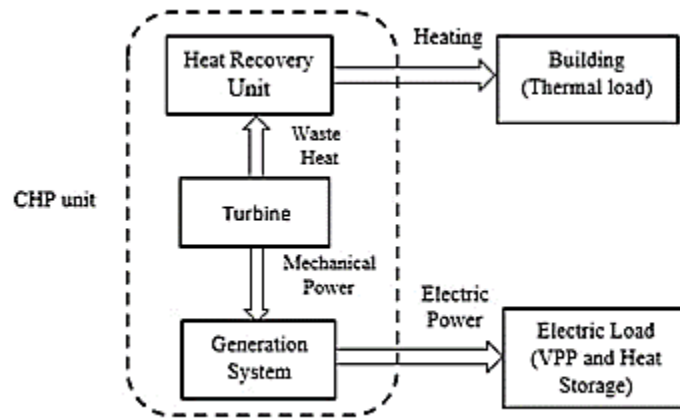


Fig. 3 Configuration of a CHP unit

When generating electricity, the CHP unit recycles heat waste to supply residential thermal loads for the improvement of a multi-energy system's overall efficiency. The ramping capability of a CHP unit makes it an ideal resource for load monitoring and frequency regulation in the proposed multi-energy system operation. Fig.3 clearly demonstrates that the outer gas network is responsible for supplying the energy hub's natural gas demands. The CHP unit's input power $\sum_m P_{m,v,w,t}^{CHP,input}$ is gas; and supplied by the gas network ($P_{v,w,t}^{gas}$) expressed in Eq. (27).

$$P_{v,w,t}^{gas} = \sum_m P_{m,v,w,t}^{CHP,input}, \forall m, \forall v, \forall w, \forall t \quad (27).$$

$$P_{m,v,w,t}^{CHP,input} = \frac{P_{m,v,w,t}^{CHP,elect}}{\eta_m^{elect}} + \frac{P_{m,v,w,t}^{CHP,heat}}{\eta_m^{heat}}, \forall m, \forall v, \forall w, \forall t \quad (28)$$

$$P_{m,v,w,t}^{CHP,elect} = P_{m,v,w,t}^{CHPelect,VPP} + P_{m,v,w,t}^{CHPelect,Heat_{storage,device}}, \quad (29)$$

$\cdot \forall m, \forall v, \forall w, \forall t.$

Equations (28) and (29) are the output power of a *CHP* with integrations of *VPP* and heat storage units to the produced electricity from *CHP* in period t for scenario v and w . It is worth noting that the heat recovery unit recovers heat produced ($P_{m,v,w,t}^{CHP,heat}$) from *CHP* and utilises same to meet end-users' heating demand only. Two conversion processes (gas to power and gas to heat) occur in the *CHP* unit of Fig.3. Also, *CHP* uses different efficiencies for the conversion of gas to electricity and heating. The inequality constraint associated with equipment capacity indicating that m^{th} *CHP* input power ($P_{m,v,w,t}^{CHP,input}$) strongly depends on maximum electricity ($P_{m,v,w,t}^{CHP,max}$) and heat

$(P_{m,v,w,t}^{CHP,heat,max})$ outputs through its efficiencies as denoted in Eq.(30).

$$P_{m,v,w,t}^{CHP,input} \leq \frac{P_{m,t}^{CHP,elect,max}}{\eta_m^{elect}} + \frac{P_{m,t}^{CHP,heat,max}}{\eta_m^{heat}}, \quad (30)$$

$$\forall m, \forall v, \forall w, \forall t.$$

The efficiencies are assumed to be the known parameters and are indicated as η_m^{elect} , η_m^{heat} . The fuel consumptions of CHP in m^3 is evaluated thus:

$$F_{CHP}(t) = \frac{P_{CHP}(t)}{\eta_e} \beta \quad (31)$$

Where $F_{CHP}(t)$ Natural gas consumption of CHP unit in period t (m^3/h), β represents a converting factor for natural gas (m^3/kWh), $P_{CHP}(t)$ represents electric power generated in period t (kW), and η_e denotes a CHP unit's electricity efficiency.

The relationship between electric power generated by $P_{CHP}(t)$ unit and recovered heat from heat recovery unit $H_{CHP}(t)$ is modelled as follows:

$$H_{CHP}(t) = P_{CHP}(t) \times \frac{\eta_{heat}}{\eta_e} \quad (32)$$

Where η_e and η_{heat} are CHP electrical and thermal efficiency, respectively.

Modelling of Heat storage unit:

The development of heat storage technologies has created a potential role for this to balance the power produced from intermittent renewable energy sources. Electricity purchased from the National grid network ($P_{v,w,t}^{elect}$) can be directly channelled to meet the heat demands of the heat storage unit. The heat storage device's input power can also be supplied from the from CHP-produced electricity ($\sum_m P_{m,v,w,t}^{CHP_{ele},Heat_{storage}}$)

by using integration multiplier ($chp - hs_m$) indicating the presence of a connection between CHP and heat storage device as expressed in Eq. (33).

$$\sum_n P_{n,v,w,t}^{HS,input} = \sum_m P_{m,v,w,t}^{CHP_{ele},HS} .chp - hs_m + P_{v,w,t}^{elec,Heat_{storage}}, \quad (33)$$

$$\forall m, \forall n, \forall v, \forall w, \forall t.$$

Injecting and drawing thermal energy from heat storage device in each time interval t cannot exceed a maximum value.

$$0 \leq H_{storage,in}(t,s) \leq \frac{H_{storage,in}^{max}}{\eta_{in}} . Y_{in}(t,s) \quad (34)$$

$$0 \leq H_{storage,dr}(t,s) \leq H_{heatstorage,dr}^{max} . \eta_{dr} . Y_{dr}(t,s) \quad (35)$$

The following equation demonstrates that in each time interval, the heat storage device is either in injecting or drawing mode:

$$Y_{in}(t,s) + Y_{dr}(s,t) \leq 1 \quad (36)$$

The upper and lower limitations of TES energy contents are formulated as follows

$$q_{heat,storage}^{min} \leq q_{heat,storage}(t,s) \leq q_{heat,storage}^{max} \quad (37)$$

The heat storage device energy content for time interval $t \geq 1$ is expressed:

$$q_{heat,storage}(t,s) = q_{heat,storage}(t-1,s) + H_{heat,storage,in}(t,s) . \eta_{in} . \Delta t - \frac{H_{storage,dr}(t,s) . \Delta t}{\eta_{dr}}, \quad t \geq 1 \quad (38)$$

Similar to electricity storage device, the following constraint is to guarantee that after a cycle of scheduling time, the energy content of heat storage device reaches the initial value:

$$q_{heat,storage}(24,s) = q_{heat,storage}(0,s) \quad (39)$$

$$\eta_{in} . \sum_{t=1}^{24} H_{heat,storage,in}(t,s) . \Delta t = \frac{\sum_{t=1}^{24} H_{heat,storage,dr}(t,s) . \Delta t}{\eta_{dr}} \quad (40)$$

Modelling of Electric Vehicle:

Active loads on today's EVs can help optimally utilize electrical energy in electric networks. They can exchange electrical power with MG network in an

economical way, based on real time electricity tariffs, so that they can be charged in off-peak hours and discharged during on-peak hours. An intelligent management of the EV charging or grid to vehicle (*G2V*) and discharging or vehicle-to-grid (*V2G*) mechanisms, entails the need to satisfy some constraints. In this research, EV is used to supply both electrical appliances and battery energy storage system inside the house, during on-peak hours. The input power of EV is represented as charging or grid to vehicle (*G2V*) condition and is expressed in Eq. 41 as:

$$\sum_n P_{v,w,t}^{EV,input,ch} = P_{v,w,t}^{pv} + P_{v,w,t}^{wind} \quad (41)$$

The PROSUMER (EV) is capable of providing electricity demand for the end-user lighting and other electrical appliances plus residential BESS charging during on-peak hours in vehicle-to-grid or discharging mode. It is expressed in Eq. 42 as:

$$P_{v,w,t}^{EV,input} = P_{v,w,t}^{BESS,end-user} + P_{v,w,t}^{end-user,elecload} \quad (42)$$

The limitations of charging and discharging of EV battery in each interval t are expressed as:

$$\begin{aligned} \frac{P_{EV,ch}^{min}}{\eta_{ch}} \cdot W_{ch}(t,s) \cdot S_{trip}(t) \\ \leq P_{EV,ch}(t,s) \leq \frac{P_{EV,ch}^{max}}{\eta_{ch}} \cdot W_{ch}(t,s) \cdot S_{trip}(t) \end{aligned} \quad (43)$$

$$\begin{aligned} P_{EV,disch}^{min} \cdot \eta_{disch} \cdot W_{disch}(t,s) \cdot S_{strip}(t) \\ \leq P_{EV,disch}(t,s) \leq P_{EV,disch}^{max} \cdot \eta_{disch} \cdot W_{disch}(t,s) \cdot S_{strip}(t) \end{aligned} \quad (44)$$

Similar to other PROSUMERS, EV battery in each interval t is either in charging or discharging mode. The following equation expresses this limitation:

$$W_{ch}(t,s) + W_{disch}(t,s) \leq 1 \quad (45)$$

$S_{trip}(t)$ is previously announced by owner of vehicle to the planner of MG. The trip signal is one when the vehicle is available and zero when it is unavailable. The upper and lower limitations of EV battery are:

$$q_{EV}^{min} \leq q_{EV}(t,s) \leq q_{EV}^{max} \quad (46)$$

For time interval $t \geq 1$, an EV's battery energy content is written as:

$$\begin{aligned} q_{EV}(t,s) = q_{EV}(t-1,s) \\ + P_{EV,ch}(t,s) \cdot \eta_{ch} \Delta t - \frac{P_{EV,disch}(t,s) \cdot \Delta t}{\eta_{disch}}, \quad t \geq 1 \end{aligned} \quad (47)$$

For guaranteeing that after a cycle of scheduling time, the energy content of an EV battery reaches its initial value, the following limitation is implemented:

$$\eta_{ch} \cdot \sum_{t=1}^{24} P_{EV,ch}(t,s) \cdot \Delta t = \frac{\sum_{t=1}^{24} P_{EV,disch}(t,s) \cdot \Delta t + q_{arrival}}{\eta_{disch}} \quad (48)$$

The equation below ensures that energy content of EV battery is maximum when the EV leaves the house:

$$q_{EV}(t_d,s) = q_{EV}^{max} \quad (49)$$

The following equation shows the stored electrical energy in EV battery after a daily trip in time t_a :

$$q_{EV}(t_a,s) = q_{arrival} \quad (50)$$

Non-dominated sorting genetic algorithm-II

Srinivas and Deb [18] introduced non-dominated sorting genetic algorithm (NSGA) to deal with multi-objective optimization problems. Non-domination is used in this algorithm, as a solutions' ranking criterion, and fitness sharing is used for diversification control in the search space. Due to the high-level sensitivity of NSGA performance to fitness sharing parameters, Deb *et al.*, [19] introduced a faster, more reliable non-dominated sorting genetic algorithm-II (NSGA-II), than its predecessor. Crowding distance is used as a second-order sorting criterion with NSGA-II. Generally, the algorithm can be described in the following steps.

Step 1. Initialize: Initially, a random parent population of size N is created.

Step 2. Fast non-dominated sorting of parent population: The population is sorted based on the non-domination. Each population is assigned a rank equal to its non-domination level or front number (1 is the best level; 2 is the next-best level and so on). Calculate the crowding distance of populations in each non-

domination level and sort populations in descending order of crowding distance.

Step 3. Tournament Selection: Select two individuals at random. Proceed by comparing their front number and crowding distance. Afterwards, select the better one and copy it to the mating pool.

Step 4. Crossover and mutation: The Simulated Binary Crossover (SBX) and polynomial mutation [20] have been used in the present work. A child population of size N is created.

Step 5. Combine the parent population and child population: The size of combined population is $2N$.

Step 6. Fast non-dominated sorting of combined population: The combined population is sorted according to non-domination and crowding distance. Since all parent and child population members are included, elitism is ensured. Populations belonging to the non-dominated set F_1 are the best in the combined populations and must be emphasized more than any other population in that subset. If the size of F_1 is smaller than N , all members of the set F_1 are chosen for the new population. The outstanding members of

the new population are chosen from subsequent non-dominated fronts in the order of their ranking. Thus, population members from the set F_2 are chosen next, followed by solutions from the set F_3 and so on. This procedure is continued until no more sets can be accommodated. That is if the set F_1 is the last non-dominated set, beyond which no other set can be accommodated. In general, the count of solutions in all sets from F_1 to F_l would be larger than population size N . To choose exactly N population, population members of the last front F_l are sorted using the crowded-comparison operator in descending order. The best population members are thus chosen to fill all slots. The new population of size N is formed.

Step 7. Stopping rule: The process can be stopped after a fixed number of generations, or when no significant improvement in the solution occurs. In this paper, NSGA-II is run for a fixed number of generations. Check for stopping criteria. If it is satisfied, then go to Step 8, else copy new population to parent population and go to Step 3.

Step 8. Stop.

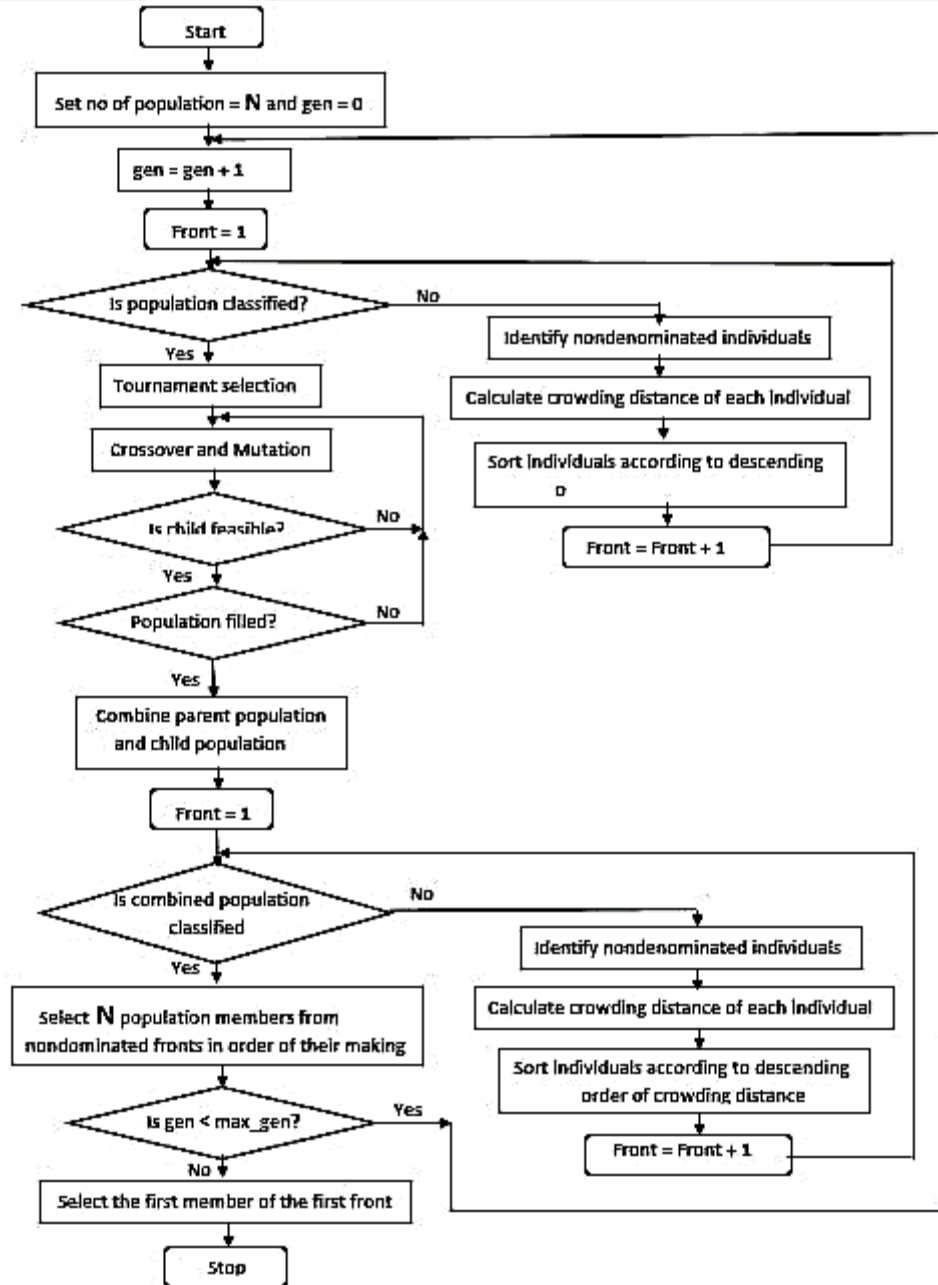


Fig. 4. Computational flow of NSGA-II.

II. CASE STUDY

In this paper, 3 cases are considered for residential building/end-users' operation. Their simulation results are compared and discussed:

Case-1 has only PV energy generation.

Case-2 has PV and wind energy generation.

Case-3 is the proposed model in this paper and has both PV, wind energy generation, BESS, TES and EVs integrated to it.

III. RESULTS AND DISCUSSION

The developed multi-energy system management model was implemented and evaluated using the Python programming framework with the PyMOO optimization library on an HP-S8ODAP computer equipped with an Intel® Core™ i3-8130U processor operating at 2.21 GHz, 8 GB RAM, and a 64-bit x64-based processor running Windows 11 Pro, Version 23H2. The performance of the two multi-objective

evolutionary optimization algorithms, namely the Nondominated Sorting Genetic Algorithm II (NSGA-II) and the Strength Pareto Evolutionary Algorithm 2 (SPEA2), was evaluated under three operating scenarios using energy expenditure and greenhouse-gas (GHG) emission as the principal performance indicators. The convergence characteristics were examined from the evolution of the best cost and emission objective values with increasing generations, while the solution quality was assessed using the

optimized energy expenditure and GHG-emission values reported in Table I. The study considers three configurations: Scenario I (Grid + PV), Scenario II (Grid + PV + Wind Turbine), and Scenario III (Grid + PV + CHP + Wind + BESS + EV). The corresponding convergence profiles are presented in Figs. 5–16, while the numerical comparison is summarized in Table I.

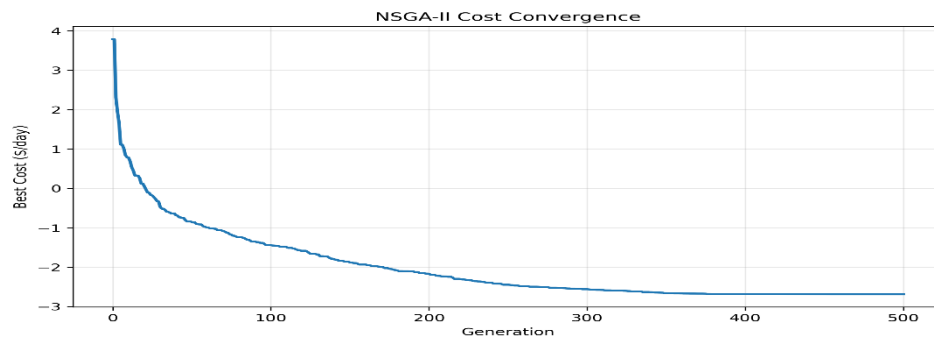


Fig. 5. NSGA-II Convergence Profile of the Cost Objective Function for Scenario I.

For Scenario I, the NSGA-II cost convergence profile exhibits a pronounced reduction in the objective value during the early generations, followed by a progressively slower rate of improvement as the optimization advances. The initial cost decreases sharply from a positive value to the negative region within the early iterations, indicating that NSGA-II rapidly identifies promising feasible solutions. Thereafter, the convergence curve becomes

increasingly gradual and approaches a stable value toward the latter part of the evolutionary process. This behavior is characteristic of an evolutionary search in which substantial improvements are obtained during the exploration stage, followed by exploitation and refinement around the near-optimal region. The corresponding NSGA-II cost convergence profile is presented in Fig. 5.

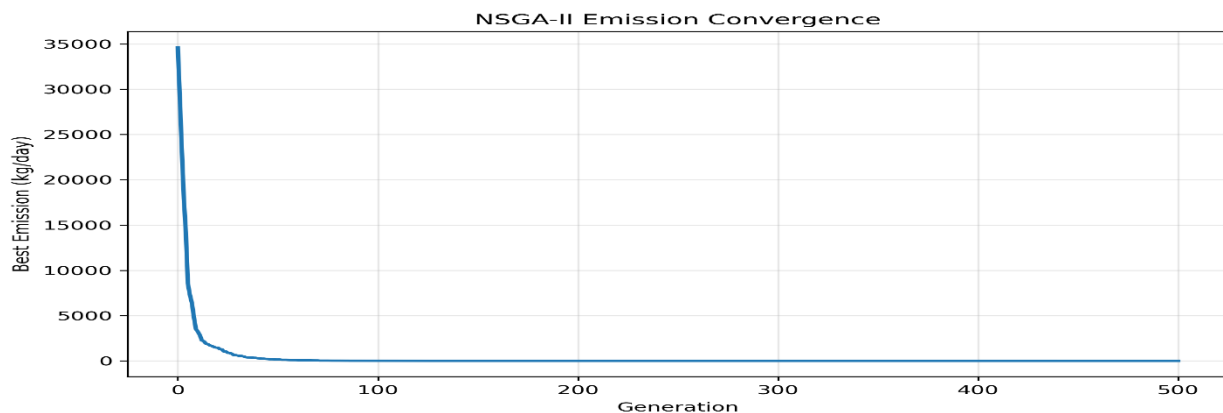


Fig. 6. NSGA-II Convergence Profile of the Emission Objective Function for Scenario I.

The NSGA-II emission convergence curve for Scenario I demonstrates an even more pronounced

initial reduction. The emission objective falls rapidly during the early generations and subsequently

approaches a near-zero level, after which only marginal improvements are observed. This indicates that the algorithm is capable of identifying solutions with very low emission levels relatively early in the optimization process. The stabilization of the curve

toward the later generations suggests that additional iterations produce limited changes in the emission objective. The associated emission convergence profile is presented in Fig. 6.

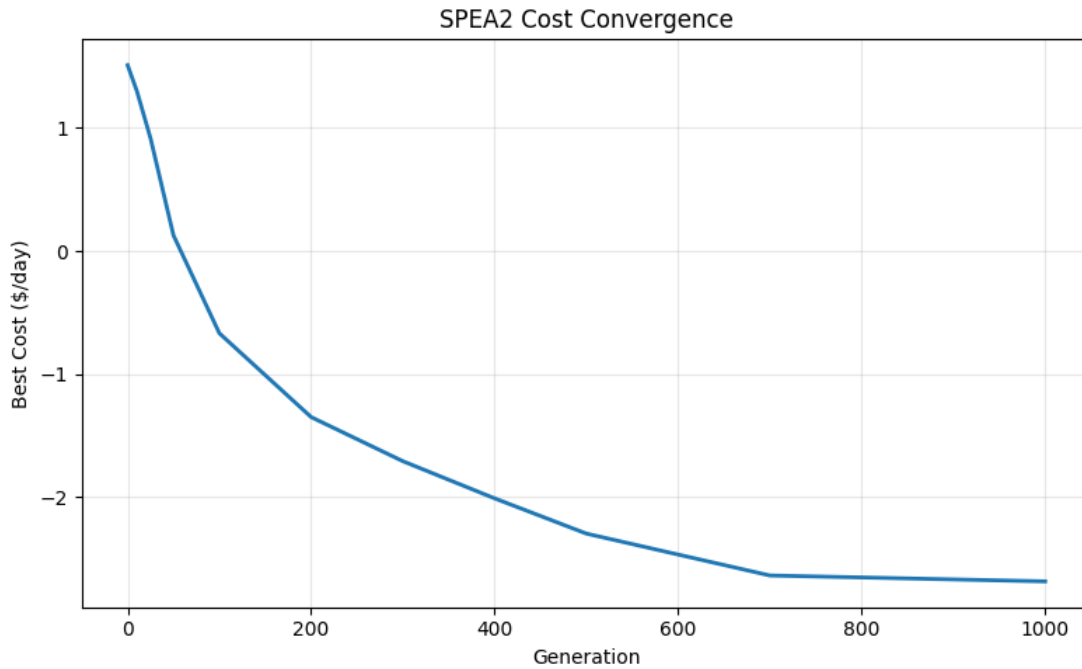


Fig. 7. SPEA2 Convergence Profile of the Cost Objective Function for Scenario I.

The SPEA2 convergence behavior is comparatively more gradual for the cost objective. The SPEA2 cost profile shows a continuous reduction in operating cost over the evolutionary process, with the rate of improvement becoming smaller as the number of generations increases. Unlike a highly abrupt convergence pattern, the curve indicates sustained refinement of the solution population and archive. The corresponding profile is shown in Fig. 7. Similarly, the

SPEA2 emission convergence profile demonstrates a substantial reduction in emissions during the initial optimization stage, followed by continued refinement toward a low-emission region. The curve approaches stabilization after the major reduction phase, indicating that SPEA2 progressively improves the quality of its nondominated solutions while maintaining diversity in the search process. The corresponding convergence profile is given in Fig. 8.

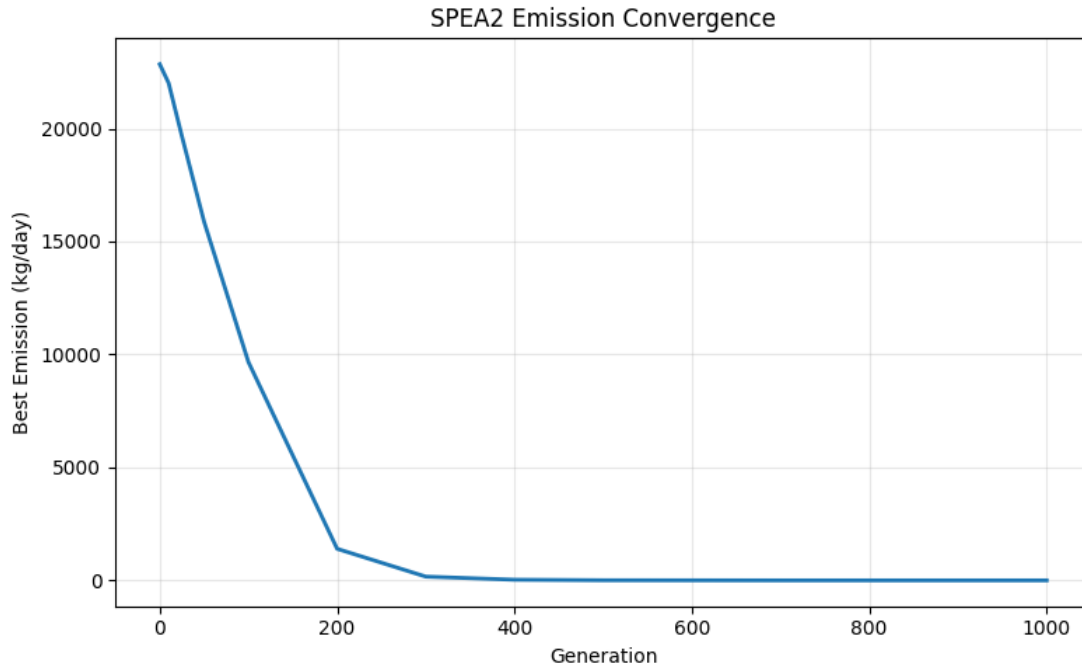


Fig. 8. SPEA2 Convergence Profile of the Emission Objective Function for Scenario I.

Numerically, Table I indicates that NSGA-II achieved an optimized energy expenditure of -2.5592 ₺/day and GHG emission of 0.00040 kg/day, whereas SPEA2 produced -1.7095 ₺/day and 166.17 kg/day, respectively. Thus, for Scenario I, the reported results show that NSGA-II simultaneously obtained a lower energy expenditure and substantially lower GHG emission than SPEA2. In particular, the emission difference is very large, indicating that the NSGA-II solution reported for this scenario lies considerably closer to the low-emission region of the objective space. The introduction of the wind turbine

in Scenario II changes the optimization landscape and produces a different convergence behavior. The NSGA-II cost convergence profile shows a rapid reduction in the early generations, followed by a smoother and progressively slower improvement toward the final generations. The curve eventually approaches a stable operating-cost region, demonstrating that the algorithm successfully exploits the additional renewable-generation resource to improve the economic operating schedule. The relevant convergence profile is presented in Fig. 9.

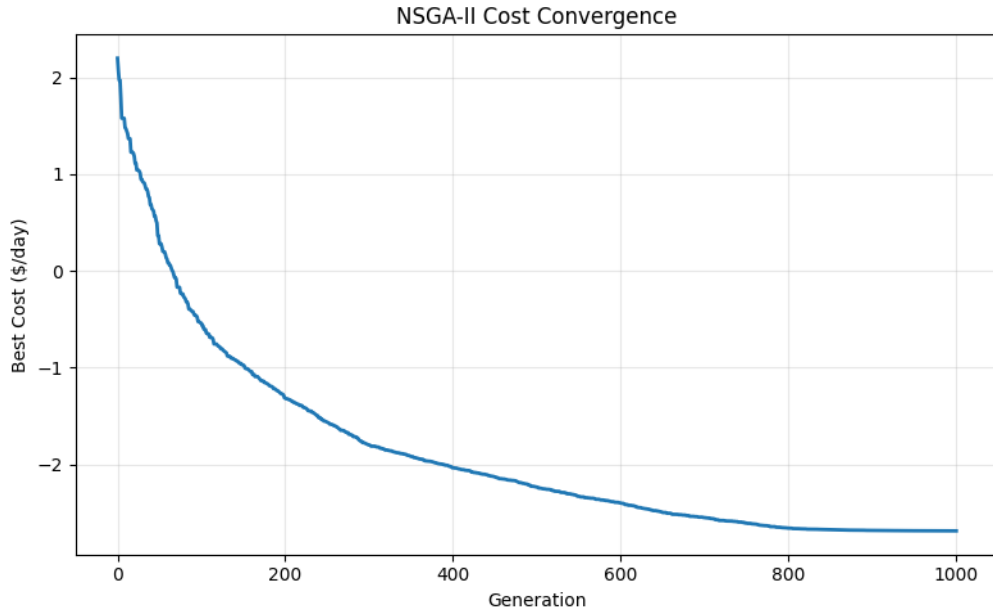


Fig. 9. NSGA-II Convergence Profile of the Cost Objective Function for Scenario II.

The corresponding NSGA-II emission curve shows a rapid decrease during the initial optimization phase, followed by a gradual approach toward an extremely low emission value. The substantial early reduction indicates that the optimization algorithm quickly identifies combinations of PV and wind generation that reduce reliance on emission-intensive energy sources. The subsequent flattening of the curve indicates convergence of the population toward a stable low-emission solution. The emission convergence profile is shown in Fig. 10. SPEA2 exhibits a comparatively stepwise convergence pattern

in Scenario II. Its cost curve shows successive reductions in the best cost rather than a continuously smooth decrease. Each reduction represents an improvement in the archived nondominated solution set, followed by periods during which the best solution remains relatively unchanged. This behavior is consistent with an archive-based evolutionary mechanism in which improvements occur when superior nondominated solutions are discovered and incorporated into the external archive. The SPEA2 cost profile is presented in Fig. 11.

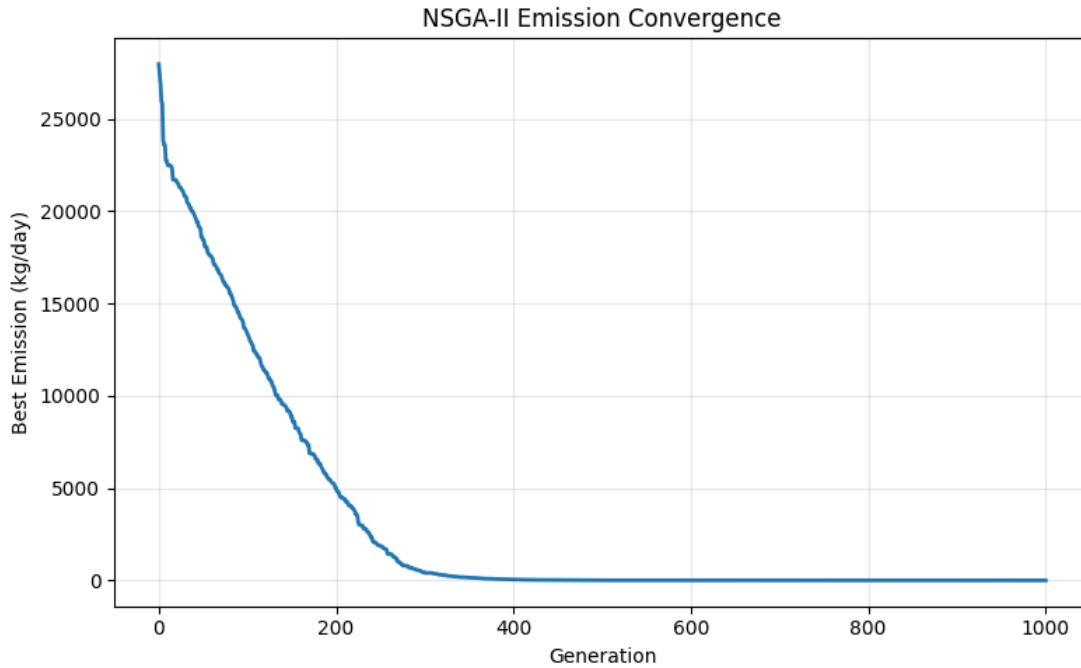


Fig. 10. NSGA-II Convergence Profile of the Emission Objective Function for Scenario II.

The SPEA2 emission convergence profile similarly demonstrates substantial reductions during the early generations, followed by progressive stabilization. The curve indicates that most of the major emission improvement occurs relatively early, while subsequent

generations contribute smaller refinements to the low-emission region. The corresponding profile is shown in Fig. 12.

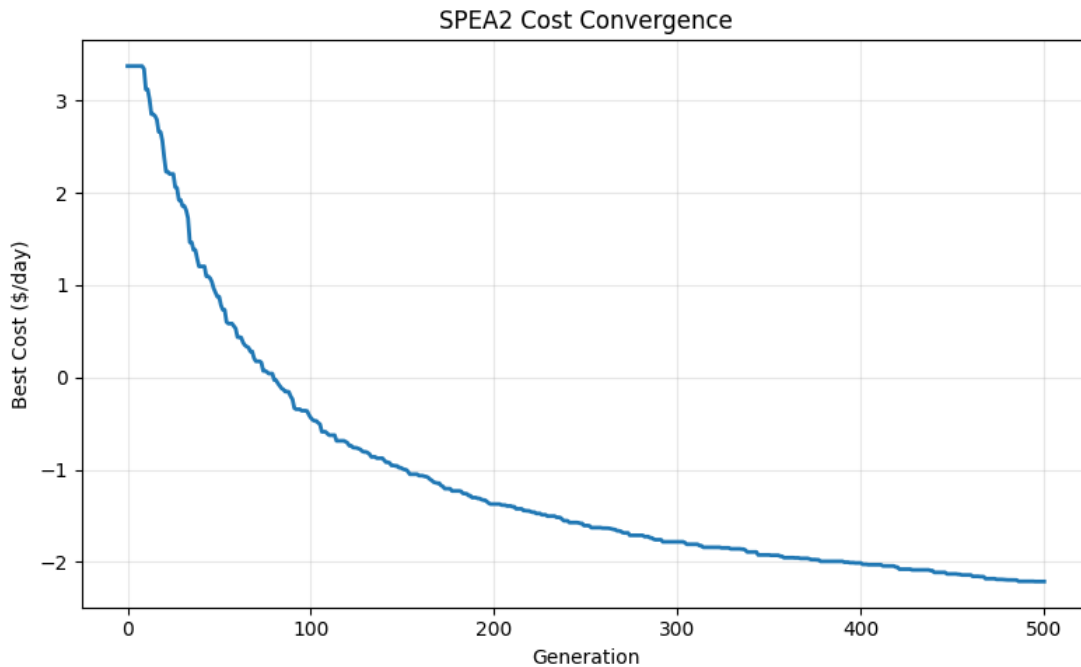


Fig. 11. SPEA2 Convergence Profile of the Cost Objective Function for Scenario II.

Table I reports an NSGA-II energy expenditure of -2.68698 ₺/day and GHG emission of 0.000296 kg/day, compared with -2.21274 ₺/day and 20.2514 kg/day for SPEA2. Therefore, the numerical results indicate that NSGA-II obtained both a lower energy expenditure and a lower GHG-emission value than SPEA2 in Scenario II. The extremely small emission value obtained by NSGA-II also demonstrates the strong influence of renewable generation on the environmental objective. Scenario III represents the most comprehensive configuration considered in the

study because it incorporates grid supply, PV generation, CHP, wind generation, battery energy storage, and electric vehicles. The NSGA-II convergence curves show continued optimization of both objectives over the evolutionary process. The cost convergence profile indicates progressive refinement toward the final economic solution, while the emission convergence profile demonstrates a corresponding reduction in the environmental objective. The relevant NSGA-II profiles are presented in Figs. 13 and 14.

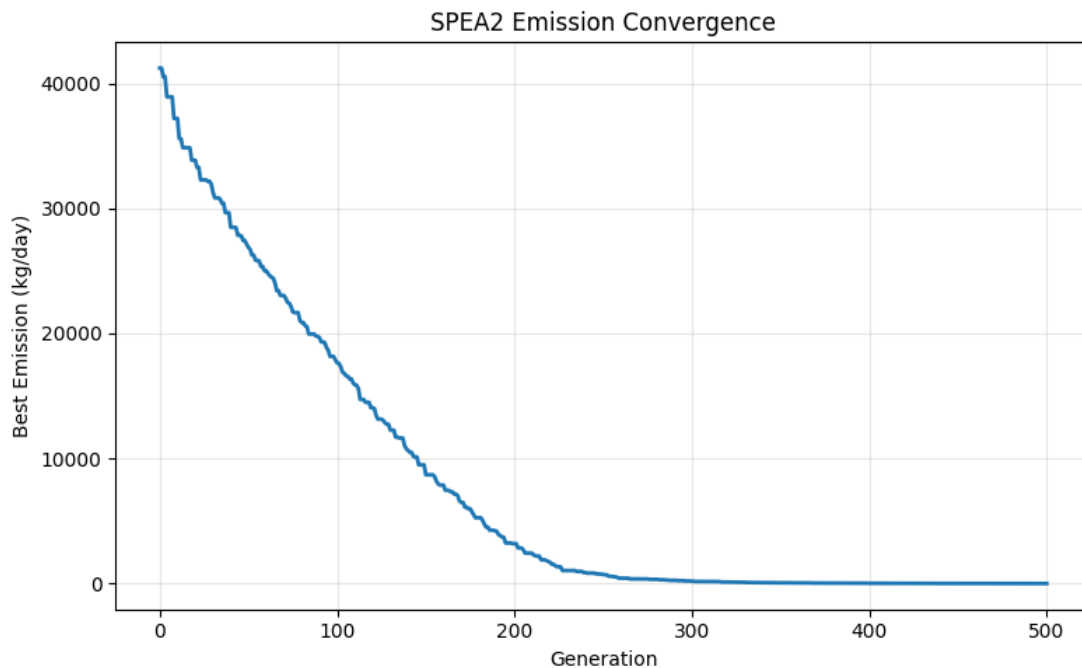


Fig. 12. SPEA2 Convergence Profile of the Emission Objective Function for Scenario II.

SPEA2 also exhibits progressive convergence for both cost and emission objectives under Scenario III. Its cost curve demonstrates successive improvements followed by stabilization, while the emission curve decreases progressively as the algorithm searches for

improved nondominated solutions. The corresponding SPEA2 convergence profiles are provided in Figs. 15 and 16.

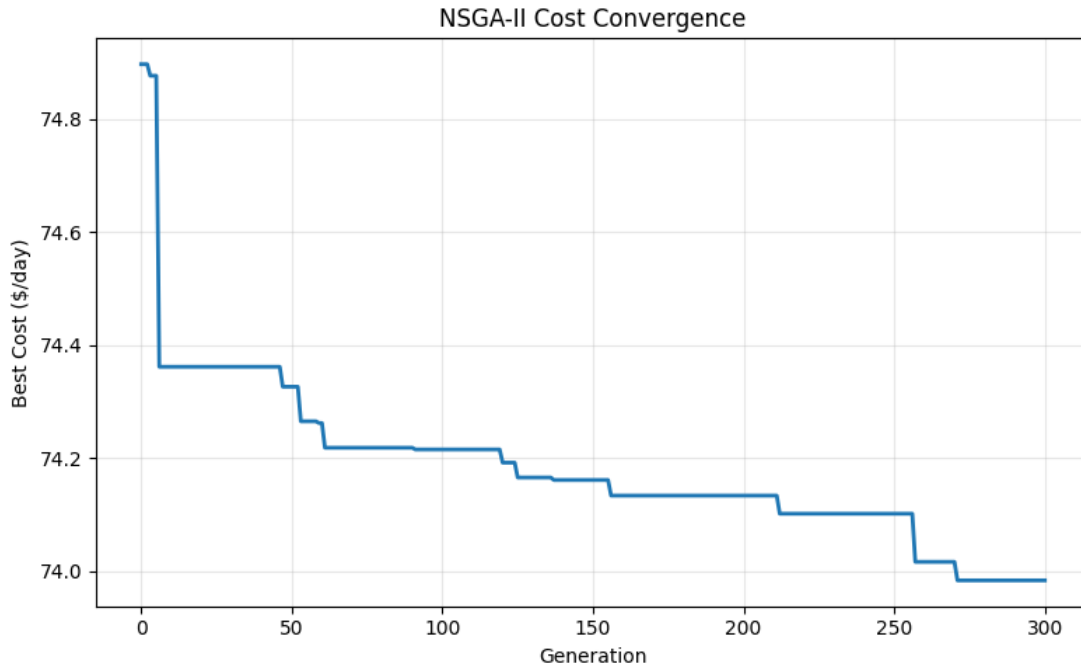


Fig. 13. NSGA-II Convergence Profile of the Cost Objective Function for Scenario III.

According to Table I, NSGA-II obtained an optimized energy expenditure of 75.93173 ₺/day and GHG emission of 142,288.66 kg/day, whereas SPEA2 obtained 76.1273 ₺/day and 141,584.79 kg/day, respectively. The results therefore show a change in the relative performance of the two algorithms compared with Scenarios I and II. NSGA-II provides the lower energy expenditure, whereas SPEA2 provides the lower GHG-emission value. This indicates that the inclusion of CHP, BESS, wind generation, and EV resources introduces a more pronounced economic–environmental trade-off, making it difficult for a single solution to

simultaneously minimize both objectives. Table I provides a direct numerical basis for comparing the solution quality of NSGA-II and SPEA2 across the three scenarios. In Scenario I, NSGA-II produces −2.5592 ₺/day, compared with −1.7095 ₺/day for SPEA2, representing an absolute difference of approximately 0.8497 ₺/day in favor of the lower reported NSGA-II cost. More importantly, the NSGA-II emission is 0.00040 kg/day, whereas SPEA2 produces 166.17 kg/day. This represents a very large difference in the reported environmental objective and demonstrates that the NSGA-II solution for Scenario I is substantially closer to the low-emission region.

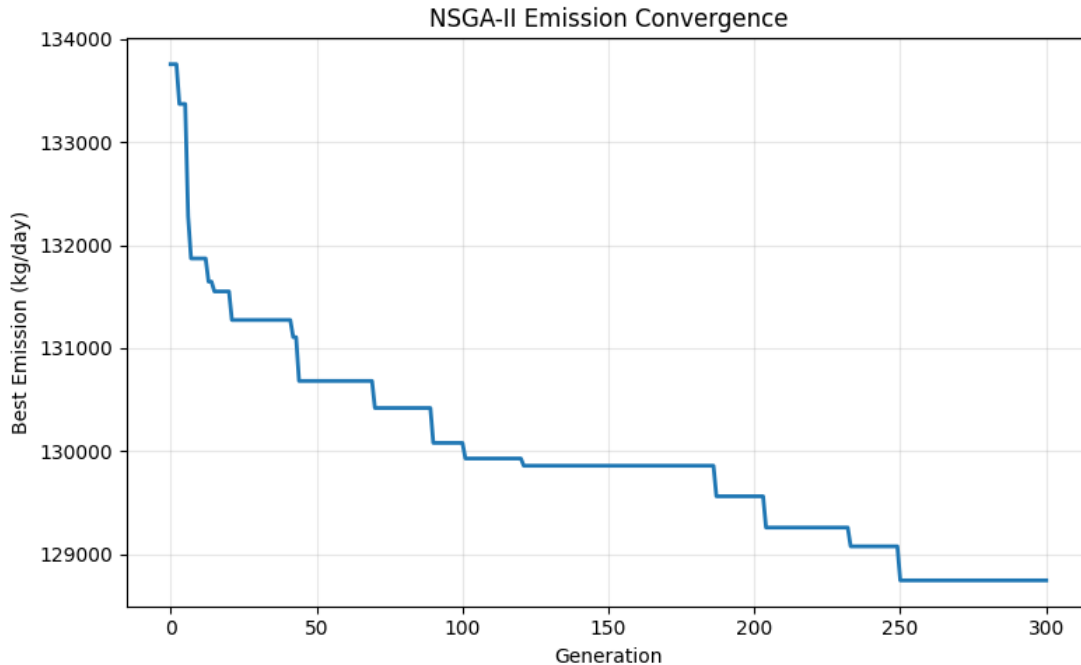


Fig. 14. NSGA-II Convergence Profile of the Emission Objective Function for Scenario III.

In Scenario II, the difference between the algorithms remains evident. NSGA-II produces -2.68698 ₺/day, while SPEA2 produces -2.21274 ₺/day. The corresponding difference is approximately 0.47424 ₺/day. The emission results are 0.000296 kg/day for NSGA-II and 20.2514 kg/day for SPEA2. Therefore, the numerical results again indicate that NSGA-II provides the lower values for both reported

performance indicators. The improvement in the emission objective from Scenario I to Scenario II is particularly notable for both algorithms, although the reduction is substantially greater for NSGA-II. Scenario III presents a different pattern. NSGA-II obtains a slightly lower cost of 75.93173 ₺/day, compared with 76.1273 ₺/day

TABLE I: Scenario-Based Assessment of Energy Cost and GHG Emissions

Case	NSGA-II Optimized Energy Expenditure (₺/day)	NSGA-II Optimized GHG Emission (kg/day)	SPEA2 Optimized Energy Expenditure (₺/day)	SPEA2 Optimized GHG Emission (kg/day)
I(Grid +PV)	-2.5592	0.00040	-1.7095	166.17
II(Grid+PV+Wind turbine)	-2.68698	0.000296	-2.21274	20.2514
III(Grid+PV+CHP+Wind+BESS+EV)	75.93173	142288.66	76.1273	141,584.79

for SPEA2, giving an absolute difference of approximately 0.19557 ₺/day. However, SPEA2 obtains a lower emission value of $141,584.79$ kg/day, compared with $142,288.66$ kg/day for NSGA-II, giving an emission difference of approximately 703.87 kg/day. Thus, the two algorithms exhibit complementary solution characteristics in Scenario

III: NSGA-II produces the lower economic objective, whereas SPEA2 produces the lower environmental objective. From the convergence profiles, both algorithms demonstrate the fundamental ability to progressively improve the objective functions rather than exhibiting uncontrolled oscillation. NSGA-II generally displays a rapid initial convergence followed

by gradual stabilization, particularly for the emission objective. This behavior suggests effective early exploration and subsequent exploitation of promising regions of the search space. SPEA2 generally exhibits progressive or stepwise improvement, reflecting the

influence of its strength-based fitness assignment and external archive in maintaining nondominated solutions. The convergence plots for the three scenarios collectively document these characteristics.

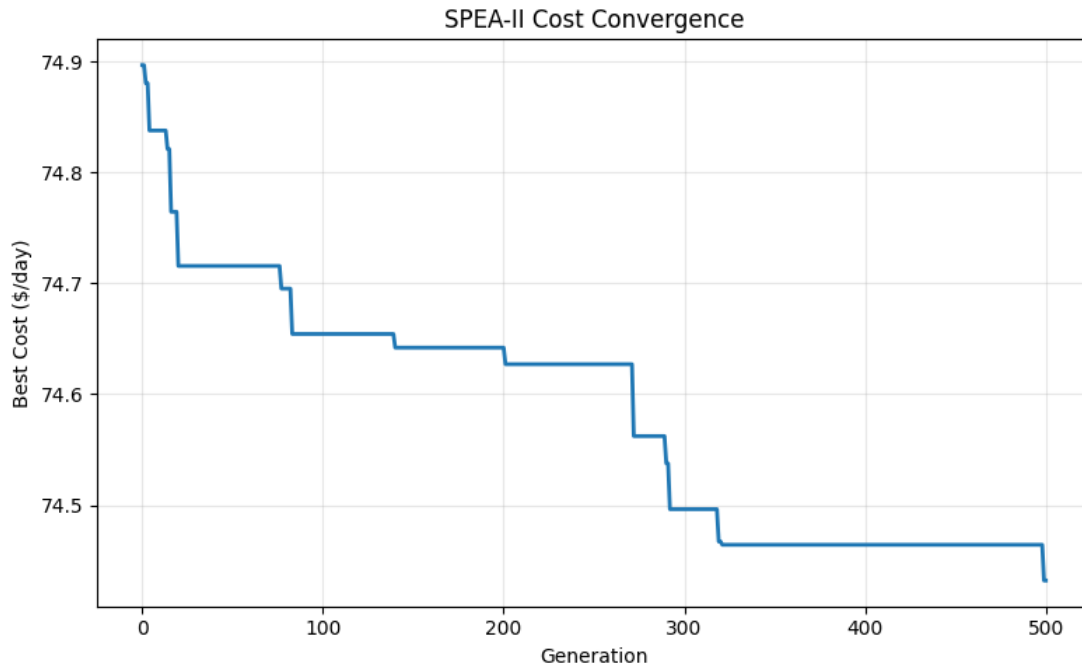


Fig. 15. SPEA2 Convergence Profile of the Cost Objective Function for Scenario III.

The numerical results further indicate that algorithmic performance is scenario-dependent rather than universally dominant. NSGA-II provides lower cost and emission values in Scenarios I and II, whereas Scenario III produces a trade-off in which NSGA-II has the lower cost and SPEA2 has the lower emission.

This change is important because it demonstrates that the relative effectiveness of an evolutionary optimization algorithm depends on the composition and operating characteristics of the energy system being optimized.

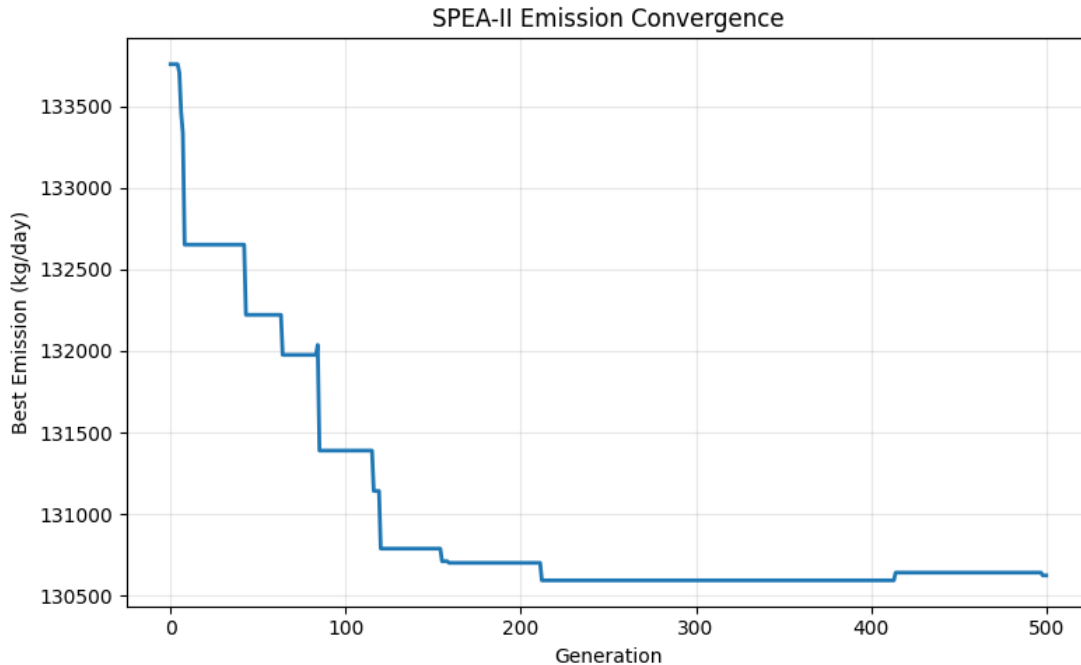


Fig. 16. SPEA2 Convergence Profile of the Emission Objective Function for Scenario III

From an economic perspective, the largest distinction between the algorithms occurs in Scenarios I and II, where NSGA-II reports lower optimized energy expenditure than SPEA2. In Scenario III, however, the difference in energy expenditure is relatively small, indicating that both algorithms identify economically competitive solutions when the system contains several interacting energy resources. From an environmental perspective, the reported values show a particularly strong advantage for NSGA-II in Scenarios I and II, while SPEA2 achieves a slightly lower emission value in Scenario III.

IV. CONCLUSION

This study developed and evaluated a multi-objective energy management framework for a residential multi-energy system (MES) integrating photovoltaic (PV), wind generation, combined heat and power (CHP), battery energy storage system (BESS), thermal energy storage (TES), electric vehicle (EV), and grid resources. The proposed framework simultaneously minimizes energy operating cost and greenhouse-gas (GHG) emissions over a 24-h scheduling horizon while satisfying the electrical and thermal power-balance equations, equipment operating limits, storage constraints, and grid-interaction requirements. The

inclusion of time-of-use (ToU) electricity pricing, natural-gas consumption, renewable-generation uncertainty, storage operation, and EV charging/discharging provides a comprehensive representation of the operational characteristics of the residential MES. The optimization performance was investigated using NSGA-II and SPEA2 under three progressively complex operating scenarios: Grid + PV, Grid + PV + Wind Turbine, and Grid + PV + CHP + Wind + BESS + EV. The convergence results demonstrate that both evolutionary algorithms progressively improved the cost and emission objectives and eventually approached stable solution regions. NSGA-II generally exhibited rapid improvement during the initial generations followed by gradual convergence, whereas SPEA2 demonstrated progressive, archive-based refinement of its nondominated solutions. These convergence characteristics confirm the capability of both algorithms to address the conflicting economic and environmental objectives of the proposed MES optimization problem. The numerical results further demonstrate that algorithmic performance depends on the operating configuration of the MES. For Scenario I, NSGA-II obtained an energy expenditure of -2.5592 ₺/day and GHG emission of 0.00040 kg/day, compared with -1.7095 ₺/day and 166.17 kg/day

obtained using SPEA2. For Scenario II, NSGA-II again produced lower values, with an energy expenditure of -2.68698 ₦/day and GHG emission of 0.000296 kg/day, while SPEA2 achieved -2.21274 ₦/day and 20.2514 kg/day, respectively. For the more comprehensive Scenario III, which incorporates PV, wind, CHP, BESS, TES, and EV resources, the results reveal a clearer economic-environmental trade-off. NSGA-II produced a slightly lower energy expenditure of 75.93173 ₦/day, whereas SPEA2 achieved a lower GHG emission of 141,584.79 kg/day, compared with 142,288.66 kg/day for NSGA-II. Multi objective for engr Sam Therefore, neither algorithm can be regarded as universally dominant across all system configurations; rather, their relative performance is influenced by the complexity and interactions among the energy resources. Overall, the study demonstrates that multi-objective evolutionary optimization can provide effective decision-support for simultaneously addressing the economic and environmental requirements of integrated residential multi-energy systems. Future research should extend the proposed framework by incorporating real-time and stochastic optimization to better represent the effects of renewable-generation and load uncertainties, particularly the variability associated with solar irradiance and wind speed.

REFERENCES

- [1] S. D. A. Karki, M. Kulkarni, M. D. Mann, and H. Salehfar, 'Efficiency improvements through combined heat and power for on-site distributed generation technologies,' *Cogeneration Distrib. Gener. J.*, vol. 22, no. 3, pp. 19–34, Jul. 2007. [Taylor & Francis](#)
- [2] D. N. Ohaegbuchi, M. S. Olaniyi, O. Dzobo, and L. Ezemonye, "Hybrid solar PV-CHP-biomass energy system modeling and optimization with battery storage impact employing differential evolution algorithm," *ASRIC Journal on Engineering Sciences*, vol. 6, no. 1, 2025.
- [3] M. Alipour, B. Mohammadi-Ivatloo, and K. Zare, "Stochastic scheduling of renewable and CHP-based microgrids," *IEEE Trans. Ind. Informat.*, vol. 11, no. 5, pp. 1049–1058, Oct. 2015.
- [4] D. N. Ohaegbuchi, O. I. Augustine, M. S. Olaniyi, I. F. Abiebhode, S. N. Ukagu, and E. N. Aneke, "Simulation and optimization of a hybridized solar PV-CHP-biomass energy system using the differential evolution algorithm," in *Proc. 2025 IEEE Connecting the Unconnected Europe, Middle East, and Africa Regional Summit (CTUS-EMEA)*, Abuja, Nigeria, 2025, pp. 1–5. [IEEE](#)
- [5] P. J. Mago, N. Furno, and L. M. Chamra, "Performance analysis of CCHP systems operating following the thermal and electric load," *Int. J. Energy Res.*, vol.33, pp.852-864, Jul. 2009.
- [6] D. N. Ohaegbuchi, O. S. Maliki, C. P. A. Okwaraoka, and H. E. Okwudiri, "Solution of combined heat and power economic dispatch problem using direct optimization algorithm," *Energy and Power Engineering*, vol. 14, no. 12, pp. 737–746, 2022. [Scientific Research Publishing](#)
- [7] J. Keirstead, N. Samsatli, N. Shah, and C. Weber, "The impact of CHP (combined heat and power) planning restrictions on the efficiency of urban energy systems," *Energy*, vol. 41, no. 1, pp. 93–103, May 2012. [ScienceDirect](#)
- [8] D. N. Ohaegbuchi, M. C. Chukwuemeka, and G. Awara, "Solution of combined heat and power economic dispatch problem using genetic algorithm," *Energy and Power Engineering*, vol. 14, no. 9, pp. 443–459, 2022. [Scientific Research Publishing](#)
- [9] K. Le, J. Golden, C. Stansberry, R. Vice, J. Wood, J. Ballance, G. Brown, J. Kamya, E. Nielsen, H. Nakajima, M. Ookubo, I. Iyoda, and G. Cauley, "Potential impacts of clean air regulations on system operations," *IEEE Trans. Power Syst.*, vol. 10, no. 2, pp. 647–656, May 1995.
- [10] D. N. Ohaegbuchi, "Solution of combined heat and power economic dispatch problem using genetic algorithm," master's dissertation, University of KwaZulu-Natal, Durban, South Africa, 2022. [Online]. Available: [University of KwaZulu-Natal](#)

- [11] Mancarella P. MES (multi-energy systems): an overview of concepts and evaluation models. *Energy* 2014;65:1e17. [ScienceDirect](#)
- [12] E. R. Ozioko, D. Ohaegbuchi, and L. Ezemonye, "Integrated modeling and energy generation optimization of a wind turbine system at Nsude Hill using a hybrid PSO-GA algorithm," SSRN preprint, 2026. [SSRN](#)
- [13] Mancarella P. MES (multi-energy systems): an overview of concepts and evaluation models. *Energy* 2014;65:1e17. [ScienceDirect](#)
- [14] D. N. Ohaegbuchi, E. F. Ayetiran, L. Ezemonye, I. A. Onyegbadue, and S. N. Ukagu, "Optimal energy management of a residential CHP–PV–wind hybrid system under escalating time-of-use tariffs," *International Journal of Applied Power Engineering (IJAPE)*, accepted for publication, 2026.
- [15] Reynolds J, Ahmad MW, Rezgui Y. Holistic modelling techniques for the operational optimisation of multi-vector energy systems. *Energy Build* 2018;169:397e416. [ScienceDirect](#)
- [16] Huang W, Zhang N, Yang J, Wang Y, Kang C. Optimal configuration planning of multi-energy systems considering distributed renewable energy. *IEEE Trans Smart Grid* 2017;3053:1e12.
- [17] Lan Y, Wu J, Guan X. Rollout strategies for real-time multi-energy scheduling in microgrid with storage system. *IET Gener, Transm Distrib* 2016;10:688e96.
- [18] Srinivas N, Deb K. Multi-objective function optimization using nondominated sorting genetic algorithms. *Evol Comput* 1995;2(3):221–48.
- [19] Deb K, Pratap A, Agarwal S, Meyarivan T. A fast and elitist multi-objective genetic algorithm: NSGA-II. *IEEE Trans Evol Comput* 2002;6(2):182–97. [IEEE](#)
- [20] Deb K, Agrawal RB. Simulated binary crossover for continuous search space. *Complex Syst* 1995;9(2):115–48.
- [21] Brahman, F., Jadid, S., 2014. Optimal energy management of hybrid CCHP and PV in a residential building. In: *Electrical Power Distribution Networks (EPDC), 2014 19th Conference on*. IEEE, pp. 19-24.
- [22] F. Y. Melhem, Z. Hammoudan, O. Grunder and N. Moubayed "Optimization and Energy Management in Smart Home Considering Photovoltaic, Wind, and Battery Storage System with Integration of Electric Vehicles" *CANADIAN JOURNAL OF ELECTRICAL AND COMPUTER ENGINEERING*, VOL. 40, NO. 2, JUNE 2, 2017.
- [23] Measurement and Instrumentation Data Center (MIDC). nd, [NREL](#). [Accessed 7 September 2023].
- [24] OpenEI datasets NREL RSF measured data. N.d, [OpenEI](#). [Accessed 7 September 2023].