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Research paper

Optimization based on movable damped wave algorithm for design of photovoltaic/ wind/ diesel/ biomass/ battery hybrid energy systems

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ABSTRACT

The actual energetic situation has several challenges such as pollution, the rarefaction of fossil fuel and the dangers of nuclear. Renewable sources are proposed as a solution and suggested, such as a cost-effectiveness system. The paper deals with the problem of feeding a domestic load with electricity which should respect the ecologies factors, so this work is a design problem of the hybrid renewable energy systems; PV/biomass, PV/diesel/battery, PV/wind/diesel/battery, and wind/diesel/battery to choose the best one of them which feed the load with the lowest cost. The study's goal is to design a microgrid system by the minimization of the total investment cost with respect to the required technical factor, the minimum allowed renewable energy fraction, and the minimum allowed availability factor. The methodology flowed utilizes frameworks based on a recent algorithm called Movable damped wave algorithm (MDVP). The proposed optimization algorithm is compared with other algorithms to prove its efficacy which are; the artificial electric field algorithm (AEFA), harris hawks optimization (HHO), and the grey wolf optimizer (GWO). The project case study is investigated in Al-Majmaah, Saudi Arabia. The contribution of this work is implementing a recent algorithm that proves its efficacy and finding the best microgrid configuration following many investigations and comparisons. The results confirm that the MDVP is better compared to the other algorithms, its computational time is fast, and its convergence is good; otherwise, the PV/biomass is considered the best configuration in the area of study with a size of 237.698 m^2 from PV panel and 954.097 t/year of biomass, which obtained the best Net Present Cost (NPC) of $299504, and a cost of energy (LCOE) assumed as $0.228/kW. A sensitivity analysis is applied to prove the effect of size variation on project factors. The simple observation, by the way, is that any change in the PV size affects the output factors.

1. Introduction

Renewable Energy Resources (RES) has been engaged in economic and sustainable development plans worldwide. In general, the RES can be integrated into the form of large generation parks connected to the main grid or in small sizes to local distribution systems. According to the kingdom's Vision 2030, Saudi Arabia included an initial target to generate 9.5 gigawatts of renewable energy (Amran et al., 2020). In this context, regulations and associated standards have been developed to accelerate the growth and strengthen the solar microgrid market (Anon, 2019). The power outage is very expensive for large consumers, like industrial facilities, large hospitals, airports, universities …, etc. The installation of microgrids could supply many loads during power outages.

The hybrid microgrids (HMGs) can give more flexibility in feeding the electricity energy, mainly for the rural regions in the world. Roy et al. (2020), Dawoud et al. (2018) present the tools of design and sizing of the microgrid, and also present some energy management strategies. Ribó-Pérez et al. (2020) presents a novel methodology for critically analyzing generation in microgrids. Wang et al. (2020) present a comprehensive study review on the modeling and operational strategies of the microgrids. Zia et al. (2018), Bukar and Tan (2019), Cagnano et al. (2020) present several energy management strategies in the Microgrid systems.

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Nomenclature

AEFA	Artificial Electric Field Algorithm
BESS	Battery energy storage system
COE	Cost of Energy
GWO	Grey Wolf Optimizer
HRES	Hybrid renewable energy system
IWO	Invasive Weed Optimization
JLBO	Jaya and teaching–learning-based optimization
NPC	Net Present Cost
PHS	Pumped hydro storage
SSO	Social spider optimizer
WT	Wind turbine
$A_{PV,WT}$	Area of PV and swept area of wind (m^2)
A_g, B_g	Constants of the linear consumption of the fuel (L/kW)
A_{pv}	PV area (m^2)
A_{wind}	Swept area of the wind turbine (m^2)
C_{BESS}	initial cost ($/kWh)
$C_{PV,WT}$	Investment cost of PV and wind generators ($)
C_{V_BM}	Calorific value of the organic material (MJ/kg)
C_{bat}	Capacity of battery (kWh)
C_{bg}	Investment cost of biomass ($)
$C_f\ (t)$	Cost of the consumed quantity of fuel ($/year)
C_{inv}	Inverter investment cost ($)
C_p	Maximum power coefficient (%)
E_{bmin}	Min battery energy in discharge (kWh)
E_l	Energy Load (kWh)
FC_{dg}	Fuel cost ($)
F_{dg}	Fuel consumption (L/h)
N_{run}	Diesel run number
OM_{BESS}	O&M (contain the replacement) costs of the BESS ($)
OM_{Inv}	O&M cost of the inverter ($)
$OM_{PV,WT}$	Operation & maintenance costs of PV and wind ($)
OM_{bg}	O&M cost of biomass ($)
OM_{dg}	Maintenance and Operation cost of diesel generator ($)
O_t	Operating hours (hr)
P_{BM}	Biomass power (kW)
P_{bg}	Rated capacity of biomass (kW)
$P_{dg,out}$	Output power of diesel generator (kW)
P_{dg}	Rated power of diesel generator (kW)
P_{inv}	Rated power of the inverter (kW)
P_{load}	Load power (kW)
P_{pv}	Output power of PV (kW)
P_r	Rated power of wind (kW)
P_{re}	Output power of renewable energy sources (kW)
P_w	Annual working of biomass system (kWh/Year)
P_{wind}	Output wind power (kW)
R_{dg}	Annual replacement cost of diesel ($)
R_{diesel}	Diesel replacement cost ($/kW)
T_{BM}	Total organic material of biomass (t/yr)
T_a	Ambient temperature (° C),
T_r	Photovoltaic cell reference temperature (° C).
i_r	Interest rate (%)
t_{max}	Maximum iteration
p_f	Fuel price ($/L)
v_{ci}	Cut-in speed (m/s)
v_{co}	Cut-out speed (m/s)
v_r	Rated wind speed (m/s)
η_{BM}	Biomass efficiency (%)
η_b	Efficiency of the battery (%)
η_i	Efficiency of the inverter (%)
η_{pv}	Efficiency of the PV (%)
η_r	Reference efficiency (%)
η_t	Efficiency of the MPPT equipment (%)
θ_1	Annual fixed cost of O&M of biomass ($/kW/year)
θ_2	Variable cost of O&M of biomass ($/kWh)
θ_{Inv}	Annual O&M cost of the inverter ($/year)
$\theta_{PV,WT}$	Annual operation & maintenance of PV and wind ($/$m^2$/year)
θ_{bat}	Annual O&M cost of BESS ($/$m^2$/year)
θ_{dg}	Annual O&M cost of diesel ($/hr)
$\lambda_{PV,WT}$	Initial cost of PV and wind ($/$m^2$)
λ_{bat}	BESS initial cost ($/kWh)
λ_{bg}	Biomass initial cost ($/kW)
λ_{dg}	Diesel initial cost ($/kW)
λ_{inv}	Inverter initial cost ($/$m^2$)
A	Availability index (%)
AD	Autonomy daily of the battery (day)
C	Investment cost ($)
CRF	Capital recovery factor
DOD	Depth of discharge (%)
I	Solar irradiation (kW/m^2)
$LCOE$	Levelized cost of energy ($/kWh)
$LPSP$	Loss of power supply probability (%)
$NOCT$	Nominal operating cell temperature (° C),
NPC	Net Present Cost ($)
OM	Operation and maintenance cost ($)
R	Replacement cost ($)
RF	Renewable Fraction (%)
v	Wind velocity (m/s)
β	Temperature coefficient of the efficiency
δ	Inflation rate (%)
μ	Escalation rate (%)
ρ	Air density (Kg/m^3)

In the recent decennia, the HMGs projects in Saudi Arabia have more attention for their considerable conditions, mainly the high irradiation. In the literature, several case studies were applied in many regions. Awan et al. (2018) presented an assessment analysis of the PV projects at 44 locations in Saudi Arabia, in which the Al-Majmaah region is considered. The analysis of data irradiation is considered for one year, and the approach used to compare the resource pattern and solar PV system output pattern with the load profile of the country. Rezk et al. (2020) designed and analyzed the PV/FC/battery HMGs; the project is dedicated to NEOM city in Saudi Arabia, characterized by high solar irradiations. The NPC and COE are constraints used to obtain the best design, using HOMER software, proving the PV is the pillar source in this system. Bouchekara et al. (2021) presented a new multi-objective algorithm MOEA/D to design a PV/Wind/Diesel hybrid system considering the load uncertainty; the project is dedicated to small houses in Yanbu, Saudi Arabia. The approach proposed gives the solution in the Pareto front, which is subject to load uncertainty. Cao et al. (2020) investigated the sizing of an HMS in Yanbu, Saudi Arabia, by minimizing three objective functions, which are costs, LPSP pollutant emissions, and the power balance. In this effect, the paper proposed an improved two-archive many-objective evolutionary algorithm (TA-MaEA) that is based on fuzzy decision technic. Fathy et al. (2022) developed a design methodology for PV, WT, battery, micro-turbines, fuel cell, and diesel based on the Sparrow Search Algorithm (SSA). The goal is to minimize COE subject to LPSP as a constraint. The SSA algorithm is compared to HHO, AEO, KH, and FSAPSO.

The HMGs are investigated and applied in many locations; this last is an important factor in precise the component of the project; Kharrich et al. (2021a) proposed a design of the PV/Wind/Diesel/Battery HMGs, dedicated for Dakhla, Morocco. The paper presented and applied a new Equilibrium Optimizer (EO) and proved its efficacy by comparing it with other algorithms such as HHO, AEFA, GWO, STOA. Guezgouz et al. (2019) introduced a new energy management strategy when using the pumped hydro storage and batteries together. The goal is to obtain an optimal size of the HMGs applied in Algeria by comparing three configurations that are: PV/wind/PSH, PV/wind/battery, and PV/wind/PSH/battery. Yu et al. (2021b) applied an adaptive version of the Marine Predators Algorithm (AMPA) in the sizing and design of the PV/battery/diesel HMGs in Hoxtolgay, China. The algorithm is used to minimize the cost and CO2. Otherwise, its effectiveness is proved by comparing it with LOA, COA, FOA, and MPA algorithms. In Kharrich et al. (2021b), a multi-objective problem is treated, which the focus is the design of a PV/wind/diesel/battery HMGs in the Rabat region of Morocco. The paper presented a new tool to compare the multi-objective algorithms to decide the best knee of point. Yu et al. (2021a) proposed an improved hybrid algorithm based on the harmony search and simulated annealing to find the best size and location of remote PV/battery schemes. The study is according to several sets of conditions such as technical, economic, social, and environmental. The case study is considered using the presented framework and compared with other heuristic methods. Houssein et al. (2022) proposed a combination of reinforcement learning (RL) with marine predator algorithm (MPA) to reduce the system investment costs of an HRES in Minia, Egypt. The proposed algorithm called Deep-MPA is used to design a hybrid renewable energy microgrid system, which contains the PV, wind turbine, diesel generator, and battery storage systems. Otherwise, these are some of the criteria and constraints required to ensure stability, robustness, performance, and load satisfaction. Zhang et al. (2021) suggested an improved algorithm for the unit's optimization and sizing of an off-grid hybrid renewable energy system composed of the wind turbine, fuel cell, and hydrogen storage systems. The objective function is the reduction of the system's total net annual cost and the LPSP. Kharrich et al. (2022) proposed an improved algorithm of IAOA; it is a modification of the Arithmetic Optimization Algorithm (AOA) using the leading operators of the Aquila Optimizer (AO). This algorithm is applied to design an HRES, composed of PV, wind turbine, diesel generator, and battery system. The objective function is to minimize the total net present cost, which includes all expenses during the project lifetime, respecting the technical, economic and ecologic aspects.

In this paper, four HMGs that are PV/Biomass, PV/wind/battery, PV/wind/diesel/battery, and wind/diesel/battery are designed, by optimizing the total project cost using a new optimization algorithm called Movable Damped Wave Algorithm (MDWA) (Rizk-Allah and Hassanien, 2018). The results are compared with AEFA, GWO, etc., to prove the proposed algorithm's ability and effeteness. Likewise, the main contributions of this paper can be summarized by the following points:

- The MDVP algorithm is applied to design a hybrid microgrid system including RES (photovoltaic, wind turbine, biomass, and battery) as well as the diesel generator.
- The reliability, availability and renewable fraction factors are considered in the designed HRES.
- The MDVP algorithm's efficiency and performance are evaluated by four design configurations, including a comparison with AEFA, HHO, GWO algorithms.
- The sensitivity analysis study is investigated to prove the effect of PV/biomass HRES size variation on the NPC, LCOE, LPSP and availability.

In the rest of this paper, the HRES modeling is presented in Section 2, while Section 3 presents the objective function and constraints, Section 4 presents the proposed optimization algorithm, Section 5 presents the case study where the project is investigated, the results and discussion are presented in Section 6, and finally, Section 6 presented the conclusion.

2. HRES modeling

The modeling of PV, wind turbine, biomass, diesel, and battery systems are presented, which the power management is divided into two strategies: PV/biomass in Fig. 1 and PV/wind/diesel/battery in Fig. 2. The goal of these strategies is to design an HRES respecting the required factors such as LPSP, renewable fraction, and availability.

Fig. 1 presents a PV/WT/diesel/battery HRES power management, firstly the load is compared with the energy produced from the renewable sources of PV and wind turbine together, if less, then the battery is charging until the maximum allowed and the dumped energy will be used otherwise. If the PV and wind turbine energies do not respond to the need, the diesel generator starts to feed power to the HRES. At the end of the flowchart, the stat of the battery is calculated to determine its level as well as the energy dumped. Likewise, Fig. 2 presents the power management of PV/biomass HRES, the energy of PV system is used to feed the load and when there is a deficiency, the biomass starts working and helps to satisfy the customer. When the power of PV is more than the power needed, the LPSP is null and the power dumped is calculated as the difference between the PV and the load demand. Otherwise, when PV generates less than the load demand, the biomass works until the working condition of 30% is validated.

In this study, the microgrid included; (1) PV, (2) wind, (3) diesel, (4) biomass, and (5) battery units. Fig. 3 presents the structure of the proposed microgrids. The system controller block diagram is represented in Fig. 4. As shown, the main power is generated from the PV and the wind units to meet the load demand. If the power from the PV and wind units with battery storage is unable to meet the energy demand, the diesel will be used to cover the lack of energy. If the energy generated using the PV and the wind systems exceeds the load demand, the excess energy will be charged using the battery. The energy generated by the PV and wind systems will serve as the heat dump when the battery storage reaches its maximum level.

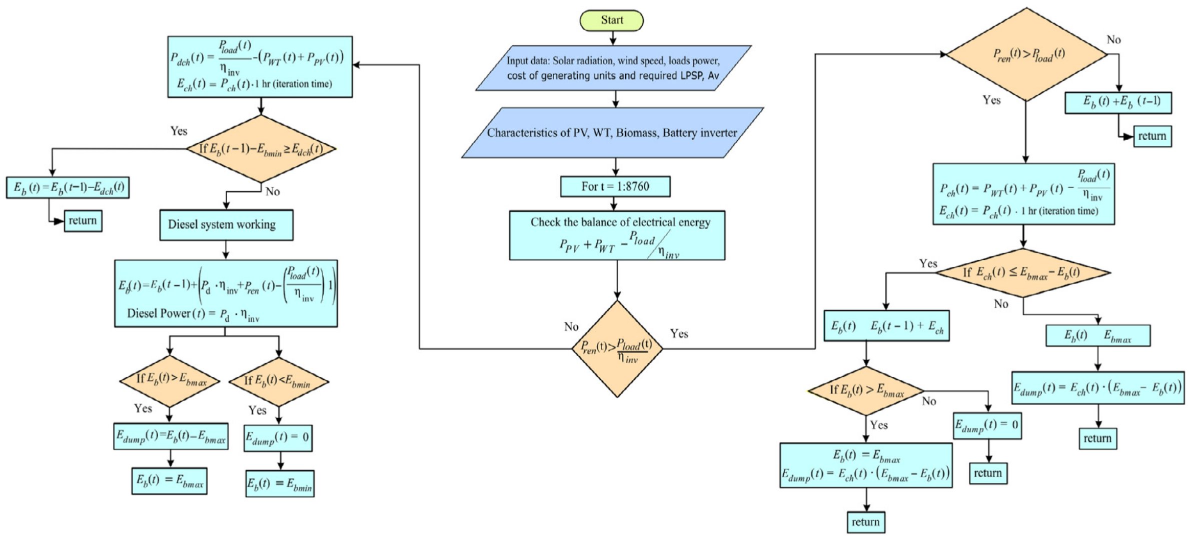


Fig. 1. Power management of the PV/WT/diesel/battery microgrid system.

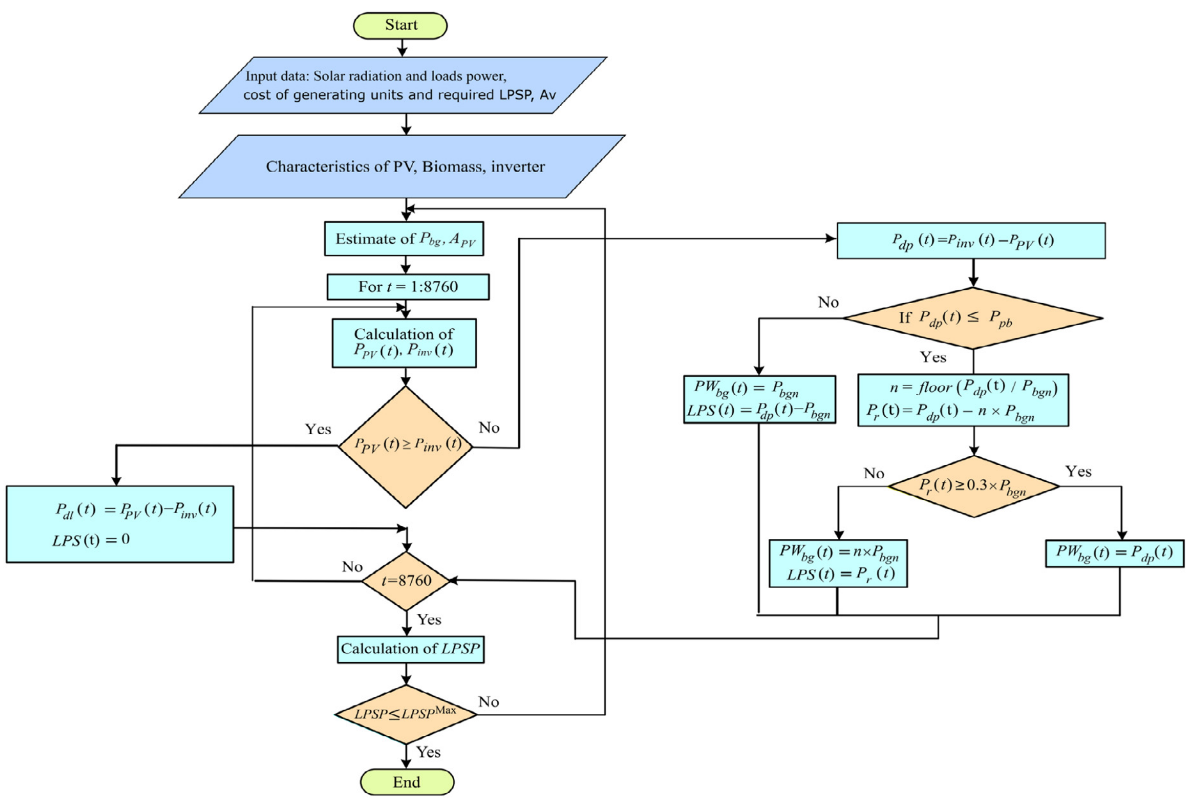


Fig. 2. Power management of the PV/biomass microgrid system.

2.1. PV panel modeling

The power of PV panel can be calculated as (Heydari and Askarzadeh, 2016; Tabak et al., 2019):

$$P_{pv} = I\langle t\rangle \times \eta_{pv}\langle t\rangle \times \boldsymbol{A_{pv}} \tag{1}$$

Where I: solar irradiation; η_{pv}: efficiency of PV; A_{pv}: PV area. The PV efficiency is calculated considering the η_r: reference efficiency; η_t: efficiency of MPPT; β: temperature coefficient; T_a: ambient temperature; T_r: PV cell reference temperature; and $NOCT$: nominal operating cell temperature.

$$\eta_{pv}(t) = \eta_r \times \eta_t \times \left[1 - \beta \times (T_a\langle t\rangle - T_r) - \beta \times I\langle t\rangle \times \left(\frac{NOCT - 20}{800}\right) \times (1 - \eta_r \times \eta_t)\right] \tag{2}$$

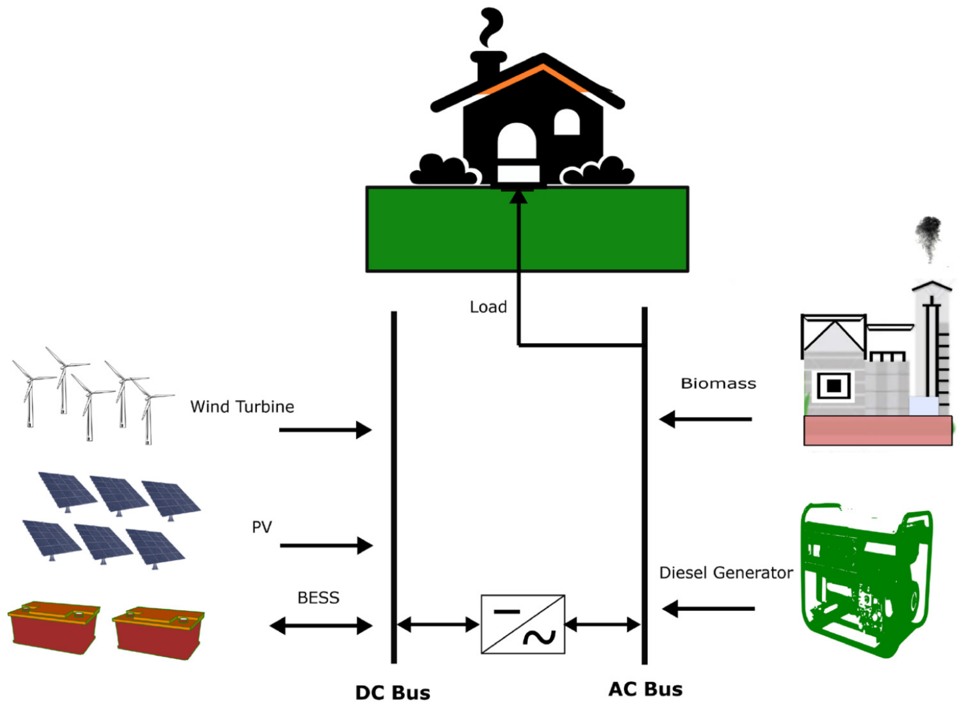


Fig. 3. The block diagram of proposed hybrid systems.

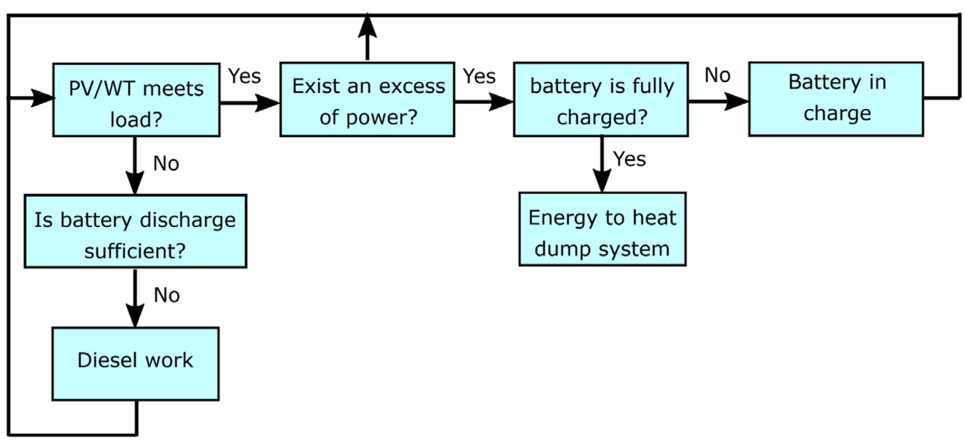


Fig. 4. The controller block diagram of PV/ Wind/ Diesel/ Battery.

2.2. Wind system modeling

The power of wind turbine can be calculated as (Guangqian et al., 2018):

$$P_{wind} = \begin{cases} 0, & v\langle t\rangle \le v_{ci}, v\langle t\rangle \ge v_{co} \\ a \times V\langle t\rangle^3 - b \times P_r, & v_{ci} < v\langle t\rangle < v_r \\ P_r, & v_r \le v\langle t\rangle < v_{co} \end{cases} \quad (3)$$

Where V: wind velocity; P_r: rated power; v_{ci}: cut-in; v_{co}: cut-out; v_r: rated wind; a and b: constant values that are expressed as:

$$\begin{cases} a = P_r / \left(v_r{}^3 - v_{ci}{}^3\right) \\ b = v_{ci}{}^3 / \left(v_r{}^3 - v_{ci}{}^3\right) \end{cases} \quad (4)$$

The rated power of the wind turbine is calculated as:

$$P_r = \frac{1}{2} \times \rho \times \boldsymbol{A_{wind}} \times C_p \times v_r{}^3 \quad (5)$$

Where ρ: air density; A_{wind}: swept area wind turbine; C_p: maximum power coefficient (from 0.25 to 0.45).

2.3. Biomass system modeling

The power of the biomass system can be calculated as (Sawle et al., 2018):

$$\boldsymbol{P_{BM}} = \frac{T_{BM} \times 1000 \times C_{V\_BM} \times \eta_{BM}}{8760 \times O_t} \quad (6)$$

Where T_{BM}: total organic material (ton/year); C_{V_BM}: the calorific value of organic material (MJ/kg); η_{BM}: biomass efficiency; O_t: operating hours for each day.

2.4. Diesel system modeling

The power of a diesel system can be calculated as (Ramli et al., 2018):

$$\boldsymbol{P_{dg}} = \frac{F_{dg}\langle t\rangle - A_g \times P_{dg,out}}{B_g} \quad (7)$$

Where F_{dg}: fuel consumption (L/hr); $P_{dg,out}$: output power of the diesel generator (Kw); A_g and B_g: constant values of fuel linear consumption (L/kWh).

2.5. Battery system modeling

The capacity of the battery system can be calculated as (Ramli et al., 2018):

$$\boldsymbol{C_{bat}} = \frac{E_l \times AD}{DOD \times \eta_i \times \eta_b} \tag{8}$$

Where E_l: load demand (kWh); AD: autonomy of the battery; DOD: depth of discharge (%); η_i: inverter efficiency (%); η_b: battery efficiency (%).

3. Objective function and constraints

3.1. Net present cost

The NPC is an economic factor considered as the objective function in this work. The focus of this paper is to minimize the NPC, which is the sum of the costs during the project lifetime (N=20 years); it is calculated as (Movahediyan and Askarzadeh, 2018; Ghiasi, 2019):

$$NPC = C + OM + R + FC_{dg} \tag{9}$$

Where C: the investment cost; OM: Operation & maintenance; R: replacement cost; FC_{dg}: fuel cost.

3.1.1. PV and WT costs

The cost modeling of PV and WT are similar. The capital cost of PV or WT ($C_{PV,WT}$) is expressed based on the initial cost ($\lambda_{PV,WT}$) and area ($A_{PV,WT}$) as follows (Ghiasi, 2019):

$$C_{PV,WT} = \lambda_{PV,WT} \times \boldsymbol{A_{PV,WT}} \tag{10}$$

The operation & maintenance costs ($OM_{PV,WT}$) are expressed as:

$$OM_{PV,WT} = \theta_{PV,WT} \times \boldsymbol{A_{PV,WT}} \times \sum_{i=1}^{N} \left(\frac{1+\mu}{1+i_r}\right)^i \tag{11}$$

where, $\theta_{PV,WT}$ is the annual operation & maintenance cost for any component, $\boldsymbol{N}$ is the project lifetime. The replacement costs are considered null because the project lifetime and the PV or WT lifetime are the same (20 years).

3.1.2. Diesel costs

The costs of the diesel generator are modeled as follows (Movahediyan and Askarzadeh, 2018):

$$C_{dg} = \lambda_{dg} \times \boldsymbol{P_{dg}} \tag{12}$$

$$OM_{dg} = \theta_{dg} \times N_{run} \times \sum_{i=1}^{N} \left(\frac{1+\mu}{1+i_r}\right)^i \tag{13}$$

$$R_{diesel} = R_{dg} \times \boldsymbol{P_{dg}} \times \sum_{i=7,14\ldots} \left(\frac{1+\delta}{1+i_r}\right)^i \tag{14}$$

$$C_f(t) = p_f \times F_{dg}\langle t\rangle \tag{15}$$

$$FC_{dg} = \sum_{t=1}^{8760} C_f\langle t\rangle \times \sum_{i=1}^{N} \left(\frac{1+\delta}{1+i_r}\right)^i \tag{16}$$

where, C_{dg} is the diesel investment cost, λ_{dg} is the initial diesel cost, OM_{dg} represents the operation and replacement cost, θ_{dg} is the annual O&M cost of diesel, N_{run} is the number of diesel-run in the year, R_{diesel} is the diesel replacement cost, R_{dg} represents the annual replacement cost of diesel, p_f is the cost of the fuel, F_{dg} is the consumed quantity of fuel and FC_{dg} is the total fuel cost. The diesel lifetime is 7 years.

3.1.3. BESS costs

The initial and O&M (contain the replacement) costs of the BESS are expressed as follows (Ghiasi, 2019):

$$C_{BESS} = \lambda_{bat} \times \boldsymbol{C_{bat}} \tag{17}$$

$$OM_{BESS} = \theta_{bat} \times \boldsymbol{C_{bat}} \times \sum_{i=1}^{T_B} \left(\frac{1+\mu}{1+\delta}\right)^{(i\_1)N_{bat}} \tag{18}$$

where, λ_{bat} is the BESS initial cost (100 \$/kWh) and θ_{bat} is the annual O&M cost of BESS (0.03*λ_{bat}). The BESS lifetime is 5 years.

3.1.4. Biomass costs

The biomass cost is represented as (Heydari and Askarzadeh, 2016):

$$C_{bg} = \lambda_{bg} \times \boldsymbol{P_{BM}} \tag{19}$$

$$OM_{bg} = \theta_1 \times \boldsymbol{P_{BM}} \times \sum_{i=1}^{N} \left(\frac{1+\mu}{1+i_r}\right)^i + \theta_2 \times P_w \times \sum_{i=1}^{N} \left(\frac{1+\mu}{1+i_r}\right)^i \tag{20}$$

where, λ_{bg} is the initial biomass cost, θ_1 is the annual fixed cost of O&M, θ_2 is the variable cost of O&M of biomass and P_w is the annual working of the system (kWh/Year). The biomass lifetime is 20 years.

3.1.5. Inverter costs

The inverter investment and O&M costs are represented as (Movahediyan and Askarzadeh, 2018):

$$C_{inv} = \lambda_{inv} \times \boldsymbol{P_{inv}} \tag{21}$$

$$OM_{Inv} = \theta_{Inv} \times \sum_{i=1}^{N} \left(\frac{1+\mu}{1+i_r}\right)^i \tag{22}$$

where, λ_{inv} is the inverter's initial cost and θ_{Inv} is the annual O&M cost of the inverter. The inverter's lifetime is 20 years.

3.2. LCOE index

The Levelized cost of energy (LCOE) is a critical economic factor that presents the price of each kWh of energy. The LCOE is calculated as (Ramli et al., 2018):

$$LCOE = \frac{NPC \times CRF}{\sum_{t=1}^{8760} P_{load}\langle t\rangle} \tag{23}$$

where CRF: Capital Recovery Factor (convert the initial cost to annual capital cost); P_{load}: Power load. The CRF is calculated as:

$$CRF(ir, R) = \frac{i_r \times (1+i_r)^R}{(1+i_r)^R - 1} \tag{24}$$

3.3. LPSP index

The LPSP is a technical index, it is used to indicate the reliability of the microgrid system. The LPSP is calculated as follows (Ramli et al., 2018):

$$LPSP = \frac{\sum_{t=1}^{8760} \left(P_{load}\langle t\rangle - P_{pv}\langle t\rangle - P_{wind}\langle t\rangle + P_{dg,out}\langle t\rangle + E_{bmin}\right)}{\sum_{t=1}^{8760} P_{load}\langle t\rangle} \tag{25}$$

3.4. Renewable energy index

Renewable energy (RF) is calculated to determine the renewable energy percent that is penetrated into the microgrid system. The RF is expressed as (Ramli et al., 2018):

$$RF = \left(1 - \frac{\sum_{t=1}^{8760} P_{dg,out}\langle t\rangle}{\sum_{t=1}^{8760} P_{re}\langle t\rangle}\right) \times 100 \tag{26}$$

where P_{re}: sum of renewable energy powers.

3.5. Availability index

The availability factor (A) is assumed as an index of the customer's satisfaction; it measures the ability of the microgrid to convert the total energy to load charge. The availability is calculated as (Ghiasi, 2019):

$$A = 1 - \frac{DMN}{\sum_{t=1}^{8760} P_{load}\langle t\rangle} \tag{27}$$

$$DMN = P_{bmin}\langle t\rangle - P_b\langle t\rangle - \big(P_{pv}\langle t\rangle + P_{wind}\langle t\rangle + P_{dg,out}\langle t\rangle - P_{load}\langle t\rangle\big) \times u\langle t\rangle \tag{28}$$

where P_{bmin}: battery min state; P_b: battery power; u: fixed value that equals 1 when the load is not satisfied and 0 otherwise.

3.6. Constraints

The constraints are introduced to tuning the microgrid system factors and help to improve the microgrid services quality. In this work, the constraints proposed are:

$$\begin{cases} 0 \le A_{pv} \le A_{pv}^{max} \\ 0 \le A_{wind} \le A_{wind}^{max} \\ 0 \le P_{dg} \le P_{dg}^{max} \\ 0 \le C_{BESS} \le C_{BESS}^{max} \\ LPSP \le LPSP^{max} \\ RF^{min} \le RF \\ A^{min} \le A \\ AD^{min} \le AD \end{cases} \tag{29}$$

4. Optimization algorithm

Actually, optimization algorithms are a very hot field, which several new, hybrid, or developed algorithms are published. Likewise, several known techniques like the Particle Swarm Optimization (PSO), Mayfly Optimization Algorithm (MA), Genetic Algorithm (GA), Invasive Weed Optimization (IWO), Cuckoo Search Algorithm (CSA), Constrained Particle Swarm Optimization (CPSO), Harmony Search Algorithm (HS), Flower Pollination Algorithm (FPA), etc.

This paper investigates and applies a new algorithm called movable damped wave algorithm (MDWA) (Rizk-Allah and Hassanien, 2018) to solve the microgrid design optimization. The proposed optimization algorithm mimics the behavior of the waveform induced through oscillating phenomena.

To improve the exploration and the exploitation, the MDWA introduced some control parameters to enhance the damped wave movable strongly; otherwise, a new parameter β is added to enable the ability of movement during the searching process. Eq. (30) summarizes this improvement as it is presented, the position of solutions $x_{i,j}^{t}$ are expressed as:

$$x_{i,j}^{t+1} = \left(\frac{\alpha}{\beta + x_{i,j}^{t}}\right) sin\left(\frac{2\pi}{\gamma}\right) x_{ij}^{t} + x_{best,j}, \qquad i = 1, 2, \ldots, PS, \tag{30}$$

Where α is responsible for the changing of damped wave amplitude, β is responsible for the wave moving to the right or the left direction, γ is responsible for contraction/expansion of the damped wave, x_{best} is the best solution and PS is the population size.

Since the three parameters are dedicated to improving the algorithm optimization, while α is the parameter that is interested to balance the exploration and exploitation, following the use of Eq. (31):

$$\alpha = a_{min} + (a_{max} - a_{min}) \times \left(\frac{t_{max} - t}{t_{max}}\right), \tag{31}$$

where t: current iteration; t_{max}: maximum iteration number; a_{min}, a_{max}: two constants, where $a_{min} = 0$ and $a_{max} = 1$.

Algorithm 1: Proposed MDVP

```
Initialize the MDWA parameters α, β and γ
Initialize the population considering LB and UB
 while (iter <iter_max)
      Calculate the fitness of each individual from the population
         Update the best solution
         Update α, β and γ
    for each individual from the population
           Update the position of all individuals using Eq. (30)
    end
                Amend the individuals based on LB and UB
 End
Return the best solution
```

5. Case study

The HRESs are investigated and applied to find a cost-effectiveness system. Four isolated configurations are considered to choose the best microgrid design: (1) PV/biomass, (2) PV/diesel/battery, (3) PV/wind/diesel/battery, and (4) wind/diesel/battery. In this fact, a recent optimization algorithm is proposed, applied, and compared to improve the robustness of the proposed algorithm. The case study is dedicated to feeding a load in the Al-Majmaah region in Saudi Arabia, as shown in Fig. 5. The input load and meteorological data are presented; Fig. 6 presents the load charge of the concerning project, and Fig. 7 presents the solar radiation, which is very good in a desert area, the same for the temperature in Fig. 8. In the rest of the meteorological data, Figs. 9–11 present wind speed, pressure, and air density, respectively.

6. Results and discussion

6.1. design and sizing of the HRES

The following work is presented to implement and test a recent algorithm and prove its efficacy and ability, for these other algorithms have been chosen to compare with it, and the application of the algorithms has been used in the complex problem

Table 1
The project data: economic and technical.

Symbol	Indice	Quantity
N	Microgrid project lifetime	20 years
i_r	Interest rate index	0.882%
μ	Escalation rate index	5%
δ	Inflation rate index	2%
PV system		
λ_{pv}	PV initial cost	400 $/m^2
θ_{pv}	Annual O&M cost of PV	$0.01 * \lambda_{pv}$ $/m^2/year
η_r	PV Reference efficiency	25%
η_t	Efficiency of MPPT	100%
T_r	reference temperature of cell PV	25 °C
β	Temperature coefficient	0.005 °C
$NOCT$	Nominal operating cell temperature	47 °C
N_{pv}	PV system lifetime	20 years
WT system		
λ_{wind}	Wind initial cost	125 $/m^2
θ_{wind}	Annual O&M cost of wind	$0.01 * \lambda_{wind}$ $/m^2/year
C_{p_wind}	Maximum power coefficient	48%
V_{ci}	Cut-in wind speed	2.6 m/s
V_{co}	Cut-out wind speed	25 m/s
V_r	Rated wind speed	9.5 m/s
N_{wind}	Wind system lifetime	20 years
Diesel generator		
λ_{dg}	Diesel initial cost	250 $/kW
θ_{dg}	Annual O&M cost of diesel	0.05 $/h
R_{dg}	Replacement cost	210 $/kW
p_f	Fuel price in Egypt	0.43 $/L
N_{diesel}	Diesel system lifetime	7 years
BESS		
λ_{bat}	Battery initial cost	100 $/kWh
θ_{bat}	Annual operation and maintenance cost of battery	$0.03 * \lambda_{bat}$ $/m^2/year
DOD	Depth of discharge	80%
η_b	Battery efficiency	97%
SOC_{min}	Minimum state of charge	20%
SOC_{max}	Maximum state of charge	80%
N_{bat}	Battery system lifetime	5 years
Inverter		
λ_{inv}	Inverter initial cost	400 $/m^2
θ_{inv}	Annual O&M cost of inverter	20 $/year
η_{inv}	Inverter efficiency	97%

Fig. 5. Project map of Al Majmaah in Saudi Arabia.

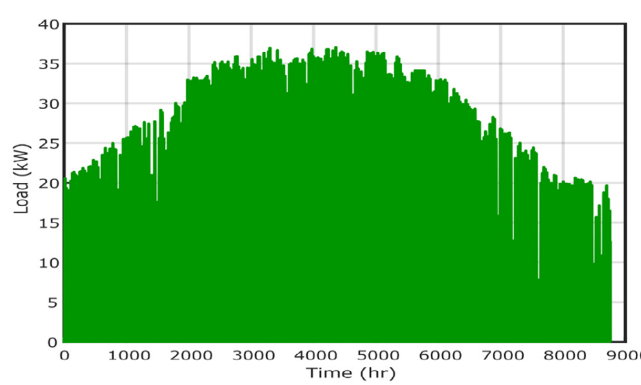


Fig. 6. Load charge of the project.

of the microgrid design, considering several aspects such as the power management, costs, and sensitivity analysis, etc.

The HRESs are investigated to feed a domestic load in Saudi Arabia. However, The research paper using a recent optimization algorithm called MDVP to prove its efficacy. Some traditional algorithms such as AEFA, HHO, and GWO are used for the comparison. The simulation is conducted using MATLAB/Editor, the PC characteristic; I5-3230M. Table 1 present the hybrid system data with the symbol, indices, and quantity. The simulation is run 100 iterations; this number is sufficient to get constant results. Table 2 present the parameters of the used algorithms.

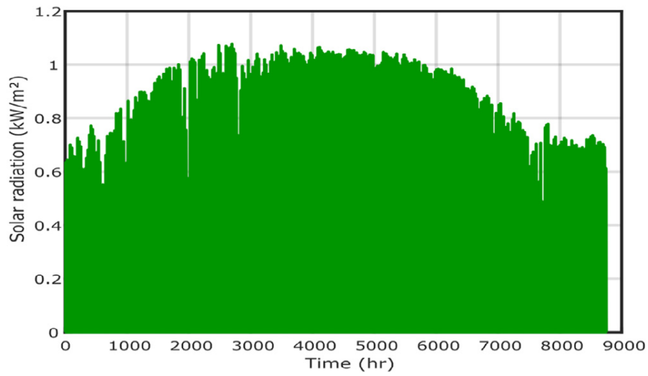


Fig. 7. Solar irradiation.

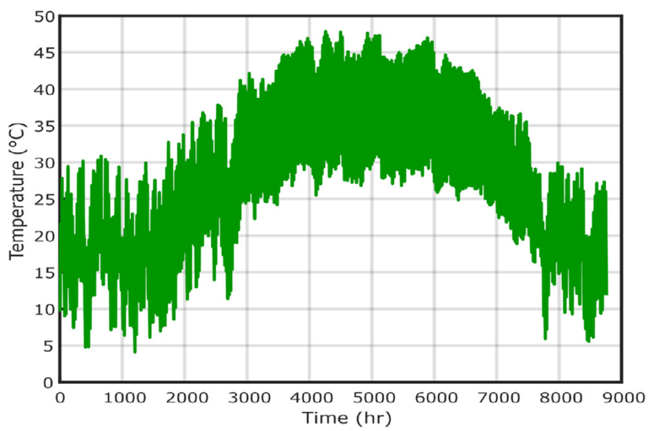


Fig. 8. Temperature data.

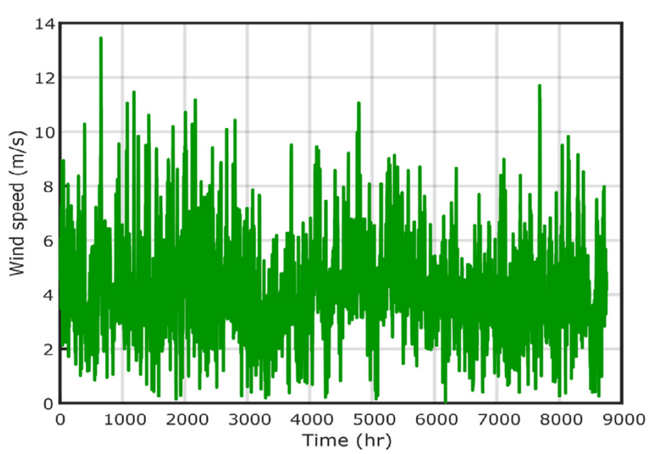


Fig. 9. Wind speed data.

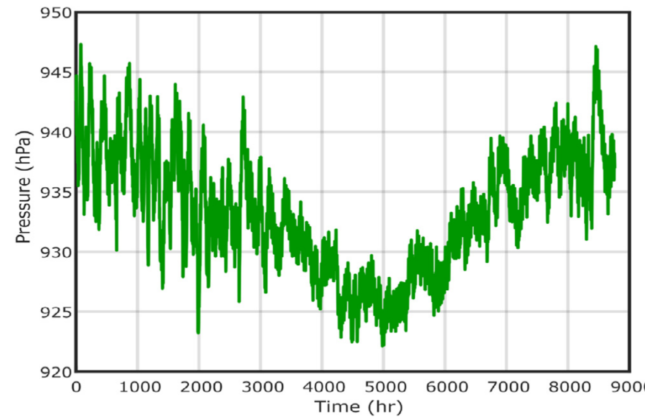


Fig. 10. Pressure data.

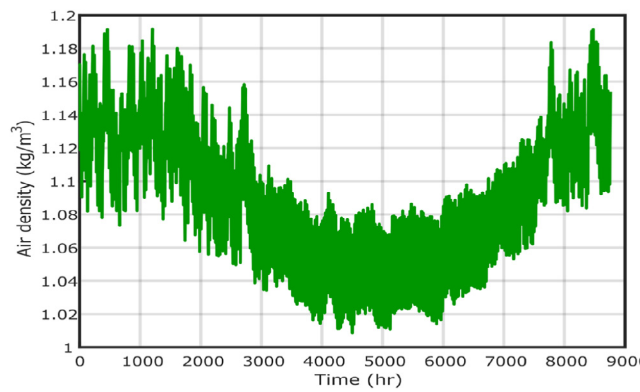


Fig. 11. Air density data.

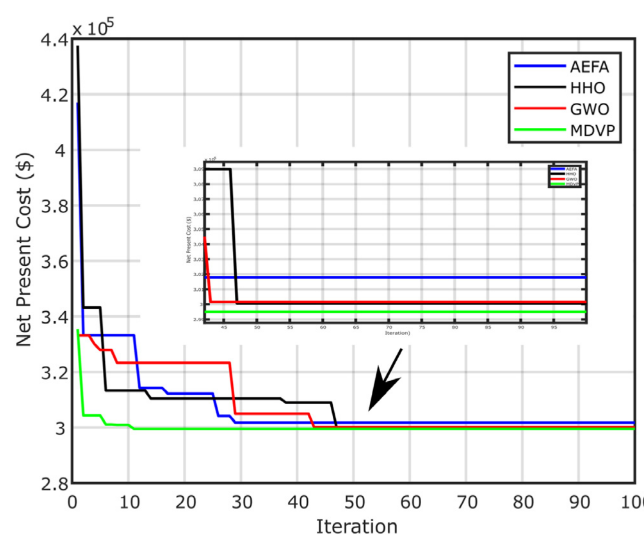


Fig. 12. NPC convergence of PV/biomass.

The results of the simulations proved the high efficiency of the proposed MDVP algorithm compared to the others. Fig. 12 shows the convergence simulation of the PV/biomass HRES, where the MDVP gets the best NPC just after 12 iterations, while AEFA in iteration 38, the HHO is converged in iteration 47 and GWO in iteration 43. The quantitative results show that the convergence is 301783, 300052, 300153, and 299504 $, respectively. Likewise, Fig. 13 presents the convergence simulation of PV/diesel/battery HRES; the convergence of MDVP is always better; otherwise, in this configuration, the AEFA gets the second better convergence; otherwise, the convergence is 482226, 489625, 486686, and 480456 $ for AEFA, HHO, GWO, and MDVP, respectively. In Fig. 14, the convergence of the PV/WT/diesel/battery HRES shows that the MDVP always converges to the best optimum solution, within 47 iterations, and the other convergence is 464958 $ for AEFA, 439738 $ for HHO, 435073 $ for GWO, and 428580 $ for MDVP. Fig. 15 shows the convergence curve of the WT/diesel/battery configuration, the best solution is always obtained by the MDVP algorithm, and this configuration is not economical compared with PV/biomass, PV/diesel/battery, and PV/WT/diesel/

Table 2
Parameters of algorithms.

Algorithms	Parameters
AEFA	$K_0 = 500$; $\alpha = 30$; Population size = 10; Maximum iteration = 100
HHO	*Beta* = 1.5 ; Population size = 10; Maximum iteration = 100
GWO	a = Linear reduction from 2 to 0; Search agents = 10; Maximum iteration = 100
MDVP	$\alpha = \alpha_{\min} + (\alpha_{\max} - \alpha_{\min}) * $ (Max_iteration-it)/Max_iteration; $\alpha_{\max} = 1$; $\alpha_{\min} = 0$; $\beta = 2 - 4 *$ rand; and $\gamma =$ rand; Population Size=10; Maximum Population Size=25; Maximum iteration = 100

battery. Otherwise, the convergence is achieved after 35 iterations, and the convergence results are 734001 $ using AEFA, 713460 $ using HHO, 749144 $ using GWO, 666580 $ using MDVP.

Table 3 presents the summarized statistical results of four algorithms which are AEFA, HHO, GWO, and MDVP, however, the microgrid configuration is; PV/biomass, PV/diesel/battery, PV/WT/diesel/battery, and WT/diesel/battery. The results show that the best-founded configuration in the case study is the PV/Biomass using the MDVP, where the best total NPC of the system is 299504 $, equivalent to 0.228 $/kWh for the cost of energy. The constraints are respected as shown in the results; in the best configuration, the LPSP is equal to 0.05, the availability is more than 95% and the system is 100% from renewable resources. For the other configurations, the PV/WT/diesel/battery HRES gets more attention than PV/diesel/battery HRES, which proves the efficacy of the synergy between the PV and the wind system. So, the proposed MDVP is improved the computational efficiency of the HRESs; likewise, the computational time is improved too, and the convergence time for the MDVP in the PV/biomass HRES is just 10910 s, while the AEFA, HHO, GWO are converged on 161908 s, 106014 s, and 209086 s, respectively. As a summary of Table 3, the NPC found is about 299504 to 749144 $, with 50% of results are close to 400000 $, and 25% more than 600000 $, and 25% less than 300000 $, while the best NPC found in the PV/biomass. The cost of energy is about 0.228 to 0.57 $/kWh, with 50% are about 0.3 $/kWh, 25% are more than 0.5% and 25% less than 0.3 $/kWh. The constraints are utmost respect; the LPSP is less than 5% in all the cases, with the best case is 1.5% in the PV/WT/diesel/battery using the AEFA algorithm, and the worst one is 5% using the MDVP algorithm in the PV/biomass configuration. The availability index is respected and has very good performances, 75% of results have more than 99%; otherwise, 25% are about 95%. The renewable fraction is more than 70% in the worst case, and 25% of results have 100% of renewable resources. For the autonomy daily of the battery is considered in the top for 4 days, in the opposite 0 when the battery is not considered. The conference time of the algorithms shows that the proposed MDVP is converge rapidly, compared to others.

Table 4 presents the summarized statistical results of the same algorithms and configuration, while this table presents the sizing results obtained, in which the MDVP algorithm finds the best HRES composed of 237.698 m^2 and a biomass system with a capacity of 954.097 tons/year. Otherwise, to analyze using qualitative and quantitative terms, the PV/ biomass configuration results are between 237 and 245 m^2 for the PV panel area, which can produce about 592.5 to 612.5 kW, that if we consider that each 1.6 m^2 produce 4 kW, which is the most popular PV systems, the biomass system needs a quantity of 954 to 976 ton/year. Hence, from the simulation results, the PV/biomass is more cost-effectiveness for this project. The second configuration of PV/diesel/battery needs a PV area between 341 to 355 m^2, a diesel capacity of 24 kW, and a battery capacity between 5 to 21 kWh, a notice that whenever the battery capacity is less the cost of the project is less too. The third configuration is the PV/WT/diesel/battery, which is considered one of the most competitive configurations; it needs between 134 to 310 m^2 of PV areas, 119 to 742 of wind swept areas, 24 to 25 kW of diesel capacity, and 0.004 to 12 kWh of battery capacity. The last configuration, which is the expensive, is composed of the wind, diesel and battery; this configuration has not used the PV, which is the most suitable in a desert region like Saudi Arabia; the sizing found for the wind is about 1076 to 1355 m^2 of wind swept area, 35 to 38 kW of the diesel capacity and a battery capacity of 0 to 42 kWh.

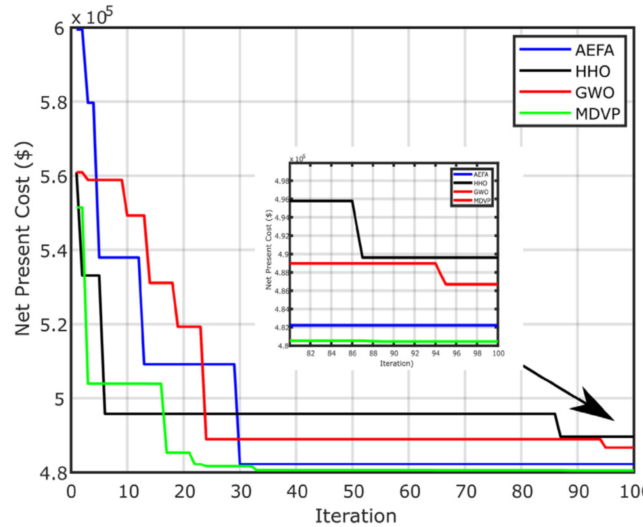


Fig. 13. NPC convergence of PV/diesel/battery.

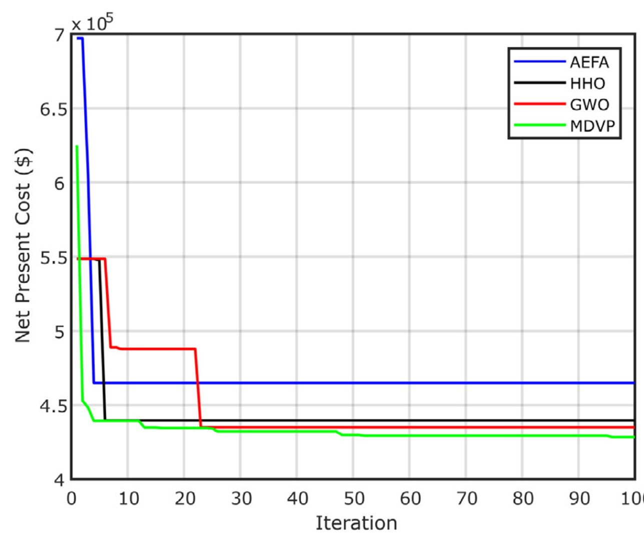


Fig. 14. NPC convergence of PV/WT/diesel/battery.

Table 3
Factor results obtained by the proposed algorithm of the four configurations.

Hybrid power system	Algorithm	NPC ($)	LCOE ($/kWh)	LPSP	Availability (%)	Renewable energy (%)	Battery autonomy (day)	Convergence time (s)
PV/biomass	AEFA	301783	0.229	0.046	95.965	100	//	161908
	HHO	300052	0.228	0.048	95.79	100	//	106014
	GWO	300153	0.228	0.048	95.78	100	//	209086
	MDVP	299504	0.228	0.05	95.875	100	//	10910
PV/diesel/battery	AEFA	482226	0.367	0.047	99.863	70.458	1.356	82073
	HHO	489625	0.373	0.042	99.894	71.719	1.193	116279
	GWO	486686	0.370	0.048	99.840	70.512	1.999	85245
	MDVP	480456	0.3661	0.049	99.887	70.844	0.517	19869
PV/WT/diesel/battery	AEFA	464958	0.3543	0.015	99.967	79.265	0.185	28626
	HHO	439738	0.335	0.045	99.861	83.761	1.19	115985
	GWO	435073	0.331	0.025	99.944	82.11	0.157	27120
	MDVP	428580	0.326	0.048	99.87	70.227	0.0003	45207
WT/diesel/battery	AEFA	734001	0.5593	0.0291	99.8648	77.2241	2.2064	63318
	HHO	713460	0.5436	0.0310	99.9504	75.8830	0.9933	106388
	GWO	749144	0.5708	0.0449	99.5509	74.2423	3.8962	63928
	MDVP	666580	0.5079	0.0490	99.9182	70.2125	0	27727

Table 4
Sizing results of the HRES configurations using AEFA, HHO, GWO and MDVP.

Hybrid power system	Algorithm	PV (m^2)	WT (m^2)	Diesel (kW)	Battery (kWh)	Biomass (t/year)
PV/biomass	AEFA	245.578	//	//	//	971.39
	HHO	239.321	//	//	//	973.302
	GWO	239.238	//	//	//	976.722
	MDVP	237.698	//	//	//	954.097
PV/diesel/battery	AEFA	341.963	//	24.689	14.776	//
	HHO	355.436	//	24.879	13	//
	GWO	344.790	//	24.923	21.788	//
	MDVP	343.844	//	24.544	5.641	//
PV/WT/diesel/battery	AEFA	310.952	175.171	25.251	2.019	//
	HHO	134.688	742.376	25.229	12.973	//
	GWO	196.791	490	24.889	1.72	//
	MDVP	245.935	119.753	24.247	0.004	//
WT/diesel/battery	AEFA	//	1355.0984	36.5955	24.0482	//
	HHO	//	1282.6173	36.034806	10.826131	//
	GWO	//	1289.1659	38.7378	42.4666	//
	MDVP	//	1076.7889	35.0255	0	//

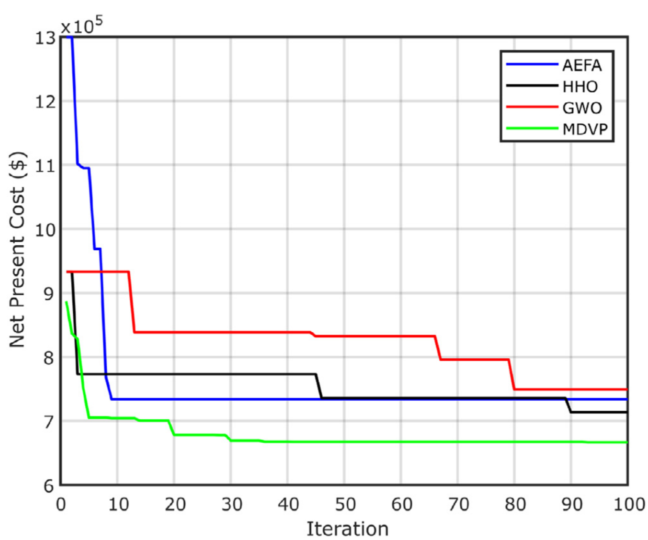


Fig. 15. NPC convergence of WT/diesel/battery.

Fig. 16 shows the hourly output power of the optimal system obtained in this study. Likewise, Fig. 17 presents the monthly power generated from the PV/biomass HRES, which shows that PV generated more than the load for multiple reasons such as respecting the constraints factors like the LPSP and availability; otherwise, the biomass produce power at a deficit moments where the PV cannot serve the load. Fig. 18 presents the monthly power generated from the PV/diesel/battery HRES, the PV produces what demand the load, then the battery stock the dumped power, for the diesel and the power discharge from the battery are used as a back-up. To manage the power flow and set the power management, the diesel and battery play an important role in satisfying the system constraints design. In Fig. 19, the wind system is introduced in power management, where it decreased the PV part and managed better the system than the PV/diesel/battery HRES.

From the above results and discussion, the authors observe that the Al-Majmaah region in Saudi Arabia country has a good condition for the implementation of hybrid renewable sources systems based on the great weather, mainly the high solar radiation, also the cheap fuel price can help in the use of diesel in order to get better system performance. From the above results, the PV, WT, biomass, diesel and battery are very useful, and any configuration between them can serve better. The PV/biomass is the better configuration with a cost of energy of 0.228 $/kWh, otherwise, the PV/WT/diesel/battery gives the electricity with 0.326 $/kWh, which can be a good solution too in this region or Saudi Arabia.

6.2. Sensitivity analysis

This paper presents a sensitivity analysis study to prove the effectiveness of the HRES sizing variation on the design factors (NPC, LCOE, LPSP and availability).

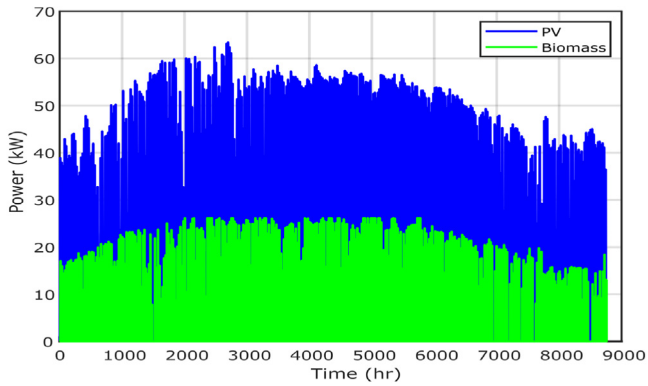


Fig. 16. Hourly Output power of the optimal configuration PV/biomass HRES.

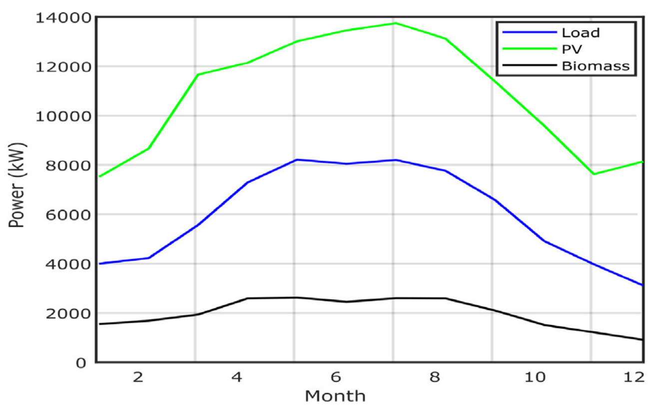


Fig. 17. Output power of PV/biomass.

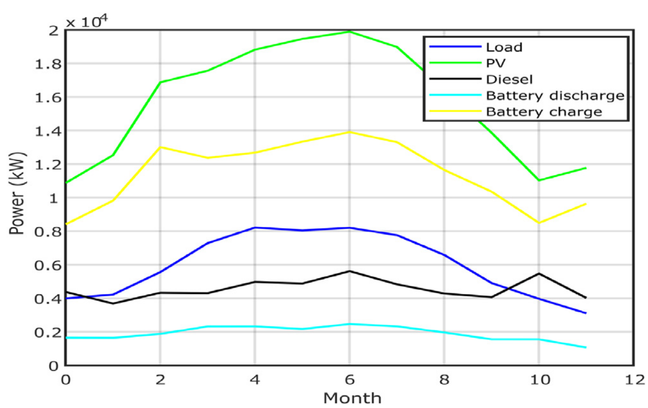


Fig. 18. Output power of PV/diesel/battery.

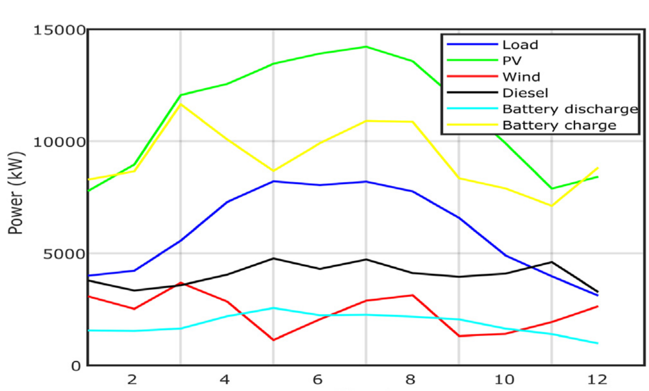


Fig. 19. Output power of PV/WT/diesel/battery.

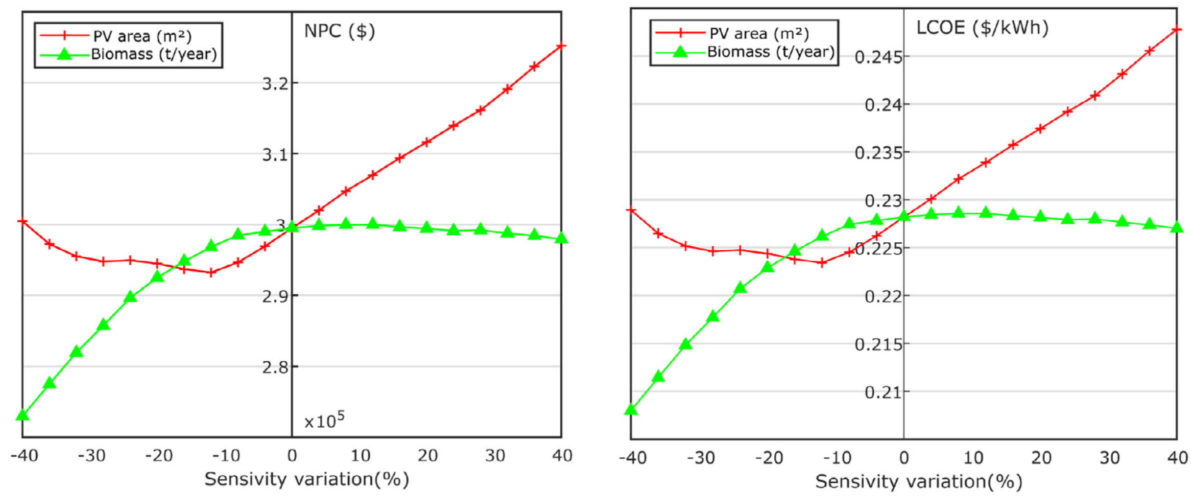
The important factors which should be considered are the NPC and LCOE; the first is our investment that depends on our budget, then the second is what the consumer should be paid; this economic information is very important for any investment. The sensitivity analysis considers the variation of the PV/biomass HRES to understand which size impacts the economic aspect of the project more. Fig. 20 shows the impact of HRES size variation on NPC and LCOE both. Fig. 20a shows that when the PV has −40% of its size, the NPC is more than 30000 $, from −40% to −13% the NPC decrease, while from −13% to +40% the NPC increases to reach more of 32500 $. Otherwise, the biomass comportment is different from the PV, mean, from −40% to 0% the NPC increases linearly, while from 0 to +40% the NPC decreases slowly. Fig. 20b presents the impact of sizing variation on LCOE. The NPC and LCOE depend on linear equations, which prove that they have both the same figure curves.

Fig. 21 shows the size variation impact of the PV/biomass HRES on the LPSP factor, which is considered the reliability factor. The results prove that the more the PV size increases the reliability is enhanced by decreasing the LPSP factor. Likewise, the biomass system variation strongly impacts the LPSP, from −40% to 0% the LPSP decreases strongly to 5%, then the reliability decreases from 0% to 40% when the biomass size increases. Fig. 22 shows the impact of the sizing variation of the PV/biomass HRES on the availability factor; the results show that the availability is more than 92% in the worst cases, which proves that the energy is available at any time. Otherwise, the variation of the PV size shows that the availability factor is not linear because of the instability of the solar radiation and also of the important dependency of the PV to generate power in this project; otherwise, the biomass capacity increases when passing from −40% to −10%, then decrease from −10% to +40%.

The authors observe that the sensitivity analysis gives us unexpected results, while the best configuration is obtained in the 0%, which considers all cases and configurations.

7. Conclusion

This paper presents and applies the recent algorithm of MDVP to design a HRES based on several units and respecting many constraints, four power management frameworks of HRES are designed: (a) PV/Biomass, (b) PV/diesel/battery, and (c) PV/WT/diesel/battery, and (d) wind/diesel/battery. The MDVP efficacy is proved by comparing its computational efficacy and time with other algorithms: AEFA, HHO, GWO, MDVP. The main objective is minimizing the NPC while respecting many constraints, which improves the HRES characteristic. The results show that the PV/biomass is the cost-effeteness HRES in the Al-Majmaah region, Saudi Arabia. Otherwise, the results are clearly proved that the proposed method got better results compared to the other literature methods. The main advantage of the proposed method is the global optimum that is very strong, which helps to find the best solution quickly. Also, the proposed method avoided the man weaknesses risen in the conventional methods like the trapped in the local search area and no equilibrium between the search processes. Likewise, the MDVP algorithm proved its superiority compared to the other algorithms. Finally, a sensitivity analysis study has been presented to prove the effectiveness of the size variation of the best-founded configuration on the sizing factors. It is observed that the more the biomass capacity is added, the more the cost of investment and cost of energy decrease.



a) Impact of sizing variation on NPC b) Impact of sizing variation on LCOE

Fig. 20. Sensitivity analysis study to prove the impact of sizing variation on (a) NPC, (b) LCOE. The configuration used is the best founded configuration of PV/biomass.

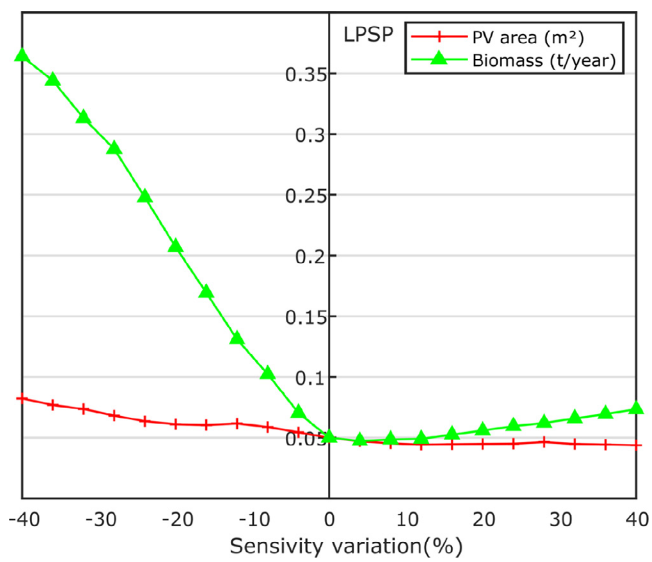


Fig. 21. Sensitivity analysis study to prove the impact of sizing variation on LPSP, the configuration used is the best founded configuration of PV/biomass.

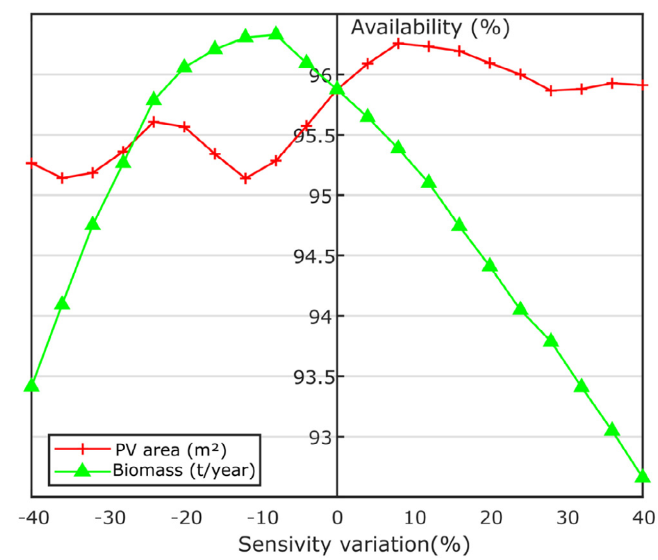


Fig. 22. Sensitivity analysis study to prove the impact of sizing variation on the availability factor, the configuration used is the best founded configuration of PV/biomass.

CRediT authorship contribution statement

Mohammed Kharrich: Data curation, Methodology, Software, Validation, Writing and reviewing. **Salah Kamel:** Data curation, Methodology, Software, Validation, Writing and reviewing. **Mamdouh Abdel-Akher:** Conceptualization, Validation, Writing – reviewing and editing. **Ahmad Eid:** Supervision, Writing – reviewing and editing. **Hossam M. Zawbaa:** Resources, Writing – reviewing and editing. **Jonghoon Kim:** Reviewing, and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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