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Optimal Energy Management Integrating Plug in Hybrid Vehicle Under Load and Renewable Uncertainties

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ABSTRACT This article introduces a robust optimal week-ahead generation scheduling approach that takes into account plug in hybrid electric vehicles (PHEVs) considering uncertainty in loads, renewable energy resources, and PHEV charging behavior. Due to the complexity of the scheduling process there is crucial need for a reliable optimal algorithm. The proposed approach can be applied in energy management platforms of decarbonized eco-friendly power systems. Generation scheduling is modeled as a multi-objective optimization problem: (a) minimize generation production cost and (b) minimize emission costs. The focal concern is to (a) handle the scheduling of renewable energy resources against their volatilities, (b) integrating PHEVs with uncertainties related to their state of charge, and (c) stochastic load behavior over a whole week. Two heuristic-based algorithms are used to solve the optimization problem, namely Water Cycle Algorithm and Gravitational Search Algorithm The proposed scheduling approach is implemented in MATLAB ®Platform, and is tested using two different microgrids sizes, 3 generator, and 10 generator unit systems integrating the effect of week days profile, renewable energy intermittency and different PHEV state of charges using the IEEE Reliability Test System (RTS) data. The results show promising performance of GSA over the WCA in the energy management studies integrating three different types of sources; thermal units, Renewable Energy Resources (RERs), and the PHEVs.

INDEX TERMS Economic dispatch (ED), gravitational search algorithm (GSA), hybrid plug in vehicle (HPEV), IEEE reliability test system, probabilistic performance, water cycle algorithm (WCA).

NOMENCLATURE AND ACRONYMS

$P_{G}i$	thermal unit output power "i" at each hour
A, B, C	the factors of the fuel cost function respectively for each thermal generating unit
N_G	the number of thermal units
P_{wind}	Wind plant output power at each hour "i"
P_{solar}	Solar plant output power at each hour "i"
A	CO2 emission factor
β	the emission penalty factor
P_{PHEV_j}	the output power of each vehicle j at hour "i"
Ψ_{dep}	the departure state of charge (DSOC)
Ψ_{min}	the discharging minimum level
Ψ_{max}	the charging up to maximum level
Ui(hour)	state of each unit "i"
X	the number of available states in each hour
N	the number of probabilities at each step
2N – 1	maximum value of X or N
Nvar	Number of design variables in the WCA algorithm
. $U^{i,hour,day}$	is the configuration on/off of each unit "i''
$SU_{H,i,day}$,, $SU_{C,i,day}$	are the cost of hot and cold startup of each unit "i'' respectively.
$t_{min,i}^{off,hour,day}$	is the minimum number of periods in hours that each unit "i'' remains in off-state
. $P_{wind/solar}^{hour,day}$	$P_{wind/solar}^{hour,day}$ is the hourly active electric power of (wind-solar) plants
$t_{min,i}^{on}$, $t_{min,i}^{off}$	are the minimum hours that the unit has to be on-line and off-line respectively.

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A_{PHEV}	is the operational cost coefficient of the batteries of PHEVs
B_{PHEV}	is the maintenance cost coefficient of the batteries of PHEVs
H	The vehicle battery efficiency
N_{V2G}	number of connected vehicles hour "i"
$N_{V2G\,max}$	the total available number of vehicles
N	number of units that are on in the unit commitment problem at each hour
N_G.	is the total number of thermal generators
$t_i^{off,hour,day}$..	is the number of periods in hours that each unit "i'' is still off until certain time "hour".
$t_{C,i}$	is the time of cold startup
$\mathrm{Price}_{\mathrm{wind/solar}}$	is a linear cost function's coefficient of wind and solar plants at each hour.
$t_i^{on,hour,day}$, $t_i^{off,hour,day}$	are the hours that the unit is on or off respectively until time period "t".
Ψ "Pres"	the present state of charge (PSOC)
Raindrop	a single solution in an array of 1 × Nvar in the WCA
NSn	the number of streams that travel towards certain rivers or the sea in the WCA.
Npop	the number of population in the WCA.
Nsr	the summation of the number of rivers in the WCA
Dmax	a small number and its value is near to zero in the WCA

I. INTRODUCTION

De-carbonization is a vital enticement behind most of the power system operation and planning studies. De-carbonization aims to reduce the amount of carbon dioxide CO2 emissions while providing improved energy services. To achieve the de-carbonization target, integrating new renewable energy resources (RERs) such as wind and solar stations and encouraging wide adoption of low carbon transportation such as Plug in Hybrid Electric Vehicles (PHEV) is needed [1]. Driven by the stochastic nature of RERs, loads, and PHEV State-of-Charge (SOC), suitable approaches are required to properly capture the RER impact on power system generation scheduling. Many studies have been presented for different multi objective problems. Application of participating RERs has been investigated for improving reliability, reducing losses, reducing production cost, and reducing emission costs in [2]–[4]. High RER penetration comes with operational challenges due to their high level of intermittency. With large scale PHEV integration, Vehicle to Grid (V2G) services can be used to cover the RER volatility based on pre-schedule table which is based on the SOC [5]–[7]. Many studies in power system nowadays consider the probability effect [8]–[10].

The problem complexity requires a robust optimization technique to solve the multi objective problem (reduce (i) generation production costs and (ii) emission costs) with respect to operational constraints, and PHEV charging constraints. Two powerful heuristic based optimization techniques, WCA and GSA, which are widely implemented in power system studies, are applied to solve the multi-objective generation scheduling problem. WCA is one of the promising heuristic optimization techniques especially in power system area. WCA has been introduced to solve optimal microgrids integration considering emission cost, reliability and loss minimization [11]–[14]. Gravitational Search Algorithm is another heuristic-based optimization technique that has been implemented for scheduling, sizing and citing of DGs [15]–[20]. Compared to the previously reported work which only considers either RERs [10] or PHEVs [13] in the scheduling problem, this article augments the RER with PHEVs, together with the impact of weekly variation of loads, RER profile and SOC of PHEVs. As such, this article presents a comprehensive unit commitment model compared to previous work.

In this article, the optimal economic dispatch problem is formulated considering intermittent and dispatchable sources. The model considers the weekly economic dispatch of all types of sources to reduce both production and emission costs. Moreover, the model includes uncertainties in daily load profiles. The proposed methodology is tested using two slandered systems integrating the effect of week days profile applying IEEE Reliability RTS, and real stochastic data [8].

The rest of the paper goes as follows. Section 2 describes the problem formulation, technical, operational, and PHEVs constraints. Section 3 presents the data of the load, source, PHEVs and the IEEE Reliability RTS. Section 4 explains the two optimization techniques (GSA and WCA) showing their point of strength and their governing parameters. Section 5 illustrates the results under different operating conditions. Section 6 concludes the results of the proposed model.

II. PROBLEM FORMULATION ALGORITHM

A. PROBLEM FORMULATION

The multi-objective function under consideration is the Average Probabilistic Economical Energy Dispatch (APEED), which can be modeled as follows:

$$\begin{aligned} \mathrm{APEED} &= \text{Minimize total cost} \\ &= \min(avarge\left\{\sum_{day=1}^{7} PEED_{day}\right\}) \end{aligned} \tag{1}$$

$$\begin{aligned} PEED_{day} &= \mathrm{sum}\{\text{Fuel cost}, \mathrm{Start_{up}cost}, \\ &\qquad \text{Shutdown cost, emission cost}\} \\ &= \sum_{i=1}^{N_G}\sum_{hour=1}^{24}\{\mathrm{Fuel}_{\mathrm{cost_{thermal}}}(P_G^{i,hour,day}) \\ &\quad +Fuel\ cost_{wind,solar}^{hour,day} + C_{PHEV}(P_{PHEV}) \\ &\quad +Startup\ cost_i^{hour,day} \times \left(1 - U^{day,hour-1}\right) \\ &\quad +Shutdown\ cost_i^{hour,day} \times \left(1 - U^{i,day,hour-1}\right) \\ &\quad +\mathrm{Emission\ cost}(\mathrm{P}^{i,,dayhour})\} \times U^{i,day,hour} \end{aligned} \tag{2}$$

- Where, *day* is a variable representing week days starting from day = 1 (Monday) and ends up with day = 7 (Sunday). The thermal units' fuel cost is defined as:

$$\text{Fuel\_cost}_{thermal} = \sum_{i=1}^{N_G} \alpha_i + \beta_i P_G^{i,day} + \gamma_i P_G^{i,day^2} \quad (3)$$

The start-up cost relies on the boilers' temperature while switching from off to on state and the time period that thermal unit was off in the previous;

$$\text{Start\_up cost}_i^{hour} = \begin{cases} SU_{H,i,day}, & t_{min,i}^{off} \leq t_i^{off,hour,day} \leq t_i^{off} + t_{C,i} \\ SU_{C,i,day}, & t_i^{off,hour,day} > t_{min,i}^{off} + t_{C,i} \end{cases} \quad (4)$$

where; Shutdown cost is generally deemed as a fixed amount.

- A linear function is used to estimate the fuel cost of RERs [10]:

$$\text{Fuel\_cost}_{\text{wind/solar}} = \text{Price}_{\text{wind/solar}} \times P_{\text{wind/solar}}^{hour,day} \quad (5)$$

- Batteries of PHEVs are considered as Battery Energy Storage Systems (BESS). The operational cost function of batteries of PHEVs is assumed to be a linear function of the absolute of its discharged power at each hour as shown[21]:

$$C_{PHEV}(P_{PEHV}) = A_{PHEV} \times P_{PHEV} + B_{PHEV} \quad (6)$$

- The emission term is considered as a linear function in the model as follows [22], [23]:

$$\text{Emission cost} = \sum_{day=1}^{7} \sum_{i=1}^{N_G} \text{A} \times 10^3 \times P_G^{i,day} \times B \quad (7)$$

- Minimum Up/Down time constraints:

Thermal generators cannot change its status instantaneously. The off-line (on-line) unit is turned on (off) after a certain number of hours called minimum down (up) time. Constraints for minimum up/down time of each generator is as shown:

$$\begin{aligned} t_i^{on,hour,day} &\geq t_{min,i}^{on} \\ t_i^{off,hour,day} &\geq t_{min,i}^{off} \end{aligned} \quad (8)$$

B. POWER BALANCE AND PHEVs OPERATING CONSTRAINTS

Thermal and RERs generators are integrated with PHEVs which can behave as loads, energy resources. as follows:

$$\begin{aligned} &\sum_{i=1}^{N_G} P_G^{i,hour,day} + P_{wind}^{hour,day} + P_{solar}^{hour,day} \\ &\quad + \sum_{j=1}^{\text{NV2G(hour)}} coofj * \eta P_{PEVj}^{hour,day} \\ &\quad \times \left[\Psi_{\text{Pres}}^{hour,day} - \Psi_{\text{dep}}^{hour,day} \right] \\ &= Demand^{hour,day} + P_{losses}^{hour,day} + Reserve^{hour,day} \end{aligned} \quad (9)$$

where coofj = 1 if the j^{th}PHEV behaves as energy resources, and -1 if it acts as a load at any given hour.

- To maintain certain amount of energy derived from PHEVs, pre-contracts are assumed to be in place between the utility and PHEV owners. This is essential for utilities to give insight knowledge about the number of vehicles connected to the grid, and their willingness to participate in grid support (Vehicle to Grid V2G Scheme). According to predetermined scheduling intervals, the electric vehicles that are registered in the smart electric network are the ones that are allowed to inject power into the grid:

$$\sum_{\text{hour}=1}^{24} \text{N}_{\text{V2G}}^{hour,day} = \text{NV2Gmax} \quad (10)$$

- To maintain the battery life:

$$\Psi_{\text{down}}^{hour,day} \text{P}_{PHEV,j} \leq P_{PHEVj}^{hour,day} \leq \Psi_{\text{up}}^{hour,day} \text{P}_{PHEV,j} \quad (11)$$

III. THREE UNIT SYSTEM

This section describes in details the data associated with the three unit test system used to prove the concept. Detailed data attributed with the ten-unit test system can be found in [30].

The first test system under study consists of 3 thermal units in addition to 2 renewable sources (Wind/Solar) and 5000 PHEV [24]. The data of the system under study can be divided into five parts:

- 3 thermal units.
- 2 renewable resources.
- 5000 PHEV.
- Emission cost coefficient data
- Weekly Load profile in hourly resolution.

A. DATA OF THE 3 THERMAL UNITS

The operational and cost data of the thermal generator units are represented in Tables 1-A, and 1-B, respectively.

TABLE 1. (A) Generator Operational Data. (B) Generator energy data.

(a)

Unit	Pmin (kW)	Pmax (kW)	Ramp up (kW/h)	Ramp down (kW/h)	Intial State
G1	30	600	200	50	On
G1	30	600	200	20	Off
G3	20	400	200	50	On

(b)

Unit	Fuel Consumption Function			Startup Cost	Shut down Cost
	α ($)	β ($/kWh)	γ ($/kWh²)	($)	($)
G1	176.	13.5	0.04	1200	800
G2	129.9	40.6	0.001	1000	500
G3	137.4	17.6	0.005	1500	800

B. DATA OF THE 2 RENEWABLE RESOURCES

Wind/Solar forecasted hourly profiles of a sample day are represented in Figures 1a and 1b, respectively [25], [26].

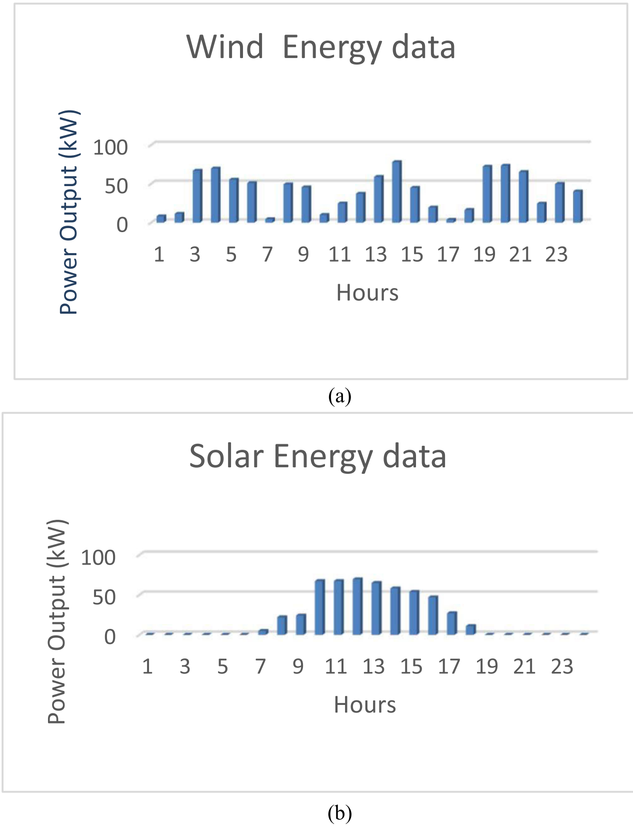

FIGURE 1. (a) Sample wind profile over the day. (b) Sample solar profile over the day.

The levelized cost of energy for wind and solar energies are assumed to be 10 \$/MWh and 14.6 \$/MWh, respectively [3].

C. DATA OF THE 5000 PHEV

The parameters of one of the 5000 PHEV units used in this study are as follows [24]:

Maximum capability of the battery	25 kW
Minimum capability of the battery	10 kW
Average capability of the battery "P_{avg}"	15 kW
Rate of charging/discharging	1 per day
Departure state of charge (SOC) "Ψ_{dep}"	50%
Efficiency "η"	85%.

D. EMISSION COST COEFFICIENT DATA

Emissions in the thermal generators are caused due to burn coal-fired fuel. Emission penalty factor "B" for the renewable power sources (wind and solar) is set at zero \$/ton CO_2. CO_2 emission factor for the PHEVs is considered for fuel oil, which is obtained from Table 2. B is the emission penalty factor in voluntary markets for planning purposes which is around 10–15 \$/ton CO2 [31]. "B" is defined to be the average of carbon prices, according to the World Bank's annual Carbon Pricing Watch Report 2017. A typical PHEV needs about 8.22 kWh/day (41.1 MWhr/day for 5000 vehicles), taking into consideration the emission factor for fuel oil from Table 2

TABLE 2. CO_2 Emission factor, A, for different energy resources [22].

Energy Resource	CO2 Emission Factor (ton/kWhr)
Wind	21.0 × 10−6
Hydro	15.0 × 10−6
Solar	6.00 × 10−6
Natural Gas	5.99 × 10−4
Fuel oil	8.93 x 10−4
Coal	9.55 ×10−4

E. LOAD PROFILE DATA

In this article the weekday/weekend effect on the load profile variability is shown in Table 3. This is based on the IEEE Reliability test system (IEEE-RTS) load profile over the week.

TABLE 3. The load profile over the week [8].

Day	Daily Peak Load (% of Weekly Peak)
Monday	93
Tuesday	100
Wednesday	98
Thursday	96
Friday	94
Saturday	77
Sunday	75

IV. OPTIMIZATION TECHNIQUES

Gravitational Search Algorithm (GSA) and Water Cycle Algorithm (WCA) have been used in several power systems optimization applications. The following two subsections describe the two algorithms.

A. GRAVITATIONAL SEARCH ALGORITHM (GSA)

Gravitational Search Algorithm (GSA) is a meta-heuristic technique revealed by Esmat Rashedi *et al.* in 2009 applying the Newtonian gravitation laws [27]. Heavier particles represent better solutions and move much slower and exert stronger attraction forces than lighter particles. To explain the mechanism of GSA:

- The spot of each of the N particles (which represent the search agents in the algorithm) in an n-dimensional space is distinct by:

$$X_i(t) = \left(x_i^1(t), x_i^2(t), \ldots\ldots\ldots, x_i^d(t), \ldots\ldots, x_i^n(t)\right) \quad for\ i = 1, 2, 3, \ldots\ldots, N \tag{12}$$

where $x_i^d(t)$ describes the location of each particle i in d-dimension at time t.

The gravitational forces between particles i and j is described by:

$$F_{ij}^d(t) = G(t)\frac{M_{pi}(t) \times M_{ai}(t)}{R_{ij} + \varepsilon}(x_j^d(t) - x_i^d(t)) \tag{13}$$

where $M_{aj}(t)$ is the mass of particle j, $M_{pi}(t)$ is the other mass of particle i, R_{ij} is the Euclidian distance between i and j and ε is a constant [27].

The gravitational constant G decays over time and is governed by the following equation:

$$G(t) = G_o e^{-\alpha t/T} \tag{14}$$

where Go and α govern the search exploration. and their quantities. T is the total number of iterations.

Then, Eq. (13) is modified as follows:

$$F_i^d(t) = \sum_{j=1, j\neq i} rand_j F_{ij}^d(t) \tag{15}$$

where $rand_j$ is a number randomly chosen between 0 and 1. The acceleration is identified as follows:

$$\alpha_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \tag{16}$$

where $M_{ii}(t)$ is the inertia mass of particle i.

Throughout the exploration, particle i informs its velocity and location as demonstrated in (17) and (18) correspondingly:

$$V_i^d(t+1) = rand_i \times V_i^d(t) + \alpha_i^d(t) \tag{17}$$

$$x_i^d(t+1) = x_i^d(t) + V_i^d(t+1) \tag{18}$$

where $rand_i$ is a number randomly chosen between 0 and 1.

In order to accomplish the optimum solution of the research problem, the following parameters are applied.

Algorithm parameter	Value
Number of agents	50
Maximum number of iterations (T)	1000
Go	100
A	20

B. WATER CYCLE OPTIMIZATION ALGORITHM (WCA)

Since 2013, WCA is used to obtain the optimal solutions for different optimization problems [20], [28], [29]. The algorithm is based on the flow of the rivers and streams into the sea, as illustrated in Figure 2.

Using the population based meta-heuristic techniques, "Raindrop" is a single solution in an array of 1 × N_ (var), where N_ (var) is the dimension of the optimization problem, i.e. the number of the design variable [28], [29]:

$$\text{Raindrop} = [X_1, X_2, X_3 \ldots X_N] \tag{19}$$

A population of raindrops is generated as a matrix of raindrops of size N_ (pop) ×N_ (var), where N_ (pop) is the number of population as per the following Equation (21):

$$\text{Population of raindrops} = \begin{bmatrix} \text{Raindrop}_1 \\ \text{Raindrop}_2 \\ \vdots \\ \vdots \\ \text{Raindrop}_{\text{Npop}} \end{bmatrix}$$

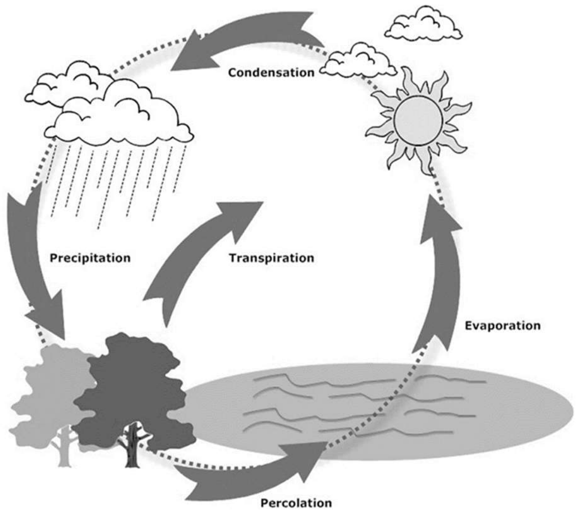

FIGURE 2. A simplified diagram of the water cycle (the hydrologic cycle) [28].

$$= \begin{bmatrix} X_1^1 & X_2^1 & X_3^1 & \ldots & X_{\text{Nvar}}^1 \\ X_1^2 & X_2^2 & X_3^2 & \ldots & X_{\text{Nvar}}^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ X_1^{\text{Npop}} & X_2^{\text{Npop}} & X_3^{\text{Npop}} & \ldots & X_{\text{Nvar}}^{\text{Npop}} \end{bmatrix} \tag{20}$$

where (X_1, X_2, X_3, X_{Nar}) are the choice variable values which may be defined as floating point number (real values) for continuous and discrete problems. The cost function of raindrops is represented in the following Equation (22):

$$C_i = \text{Cost}_i = f(X_1^i, X_2^i, X_3^i, \ldots, X_N^i), i = 1, 2, 3, \ldots, \text{N}_{\text{pop}}. \tag{21}$$

Seas and rivers are chosen as minimum values (the best individuals). Nsr is defined as the summation of the number of rivers. The other raindrops (population) flow either to the rivers or directly to the sea as per the following equations:

$$\text{N}_{\text{sr}} = \text{Number of Rivers} + 1, \text{ where 1 is for one sea} \tag{22}$$

$$\text{N}_{\text{Raindrops}} = \text{N}_{\text{pop}} - \text{N}_{\text{sr}} \tag{23}$$

The intensity of the flow determines how to assign raindrops to the rivers and the sea as follows:

$$\text{N}_{\text{sn}} = \text{round}\left\{\left|\frac{Cost_n}{\sum_{i=1}^{Nsr} Cost_i}\right| \times \text{N}_{\text{Raindrops}}\right\}, \ \text{n} = 1, 2 \ldots, \text{N}_{\text{sr}}. \tag{24}$$

where N_(sn) is defined as the number of streams, which travels towards certain rivers or the sea. Figure 3 describes the WCA optimization process in which X is the distance between the stream and the river, can be randomly chosen as follows:

$$X \in (0, C \leq d), \quad 1 < C < 2 \tag{25}$$

where d is the current distance between stream and river. The value of X in Equation (25) is set according to a randomly

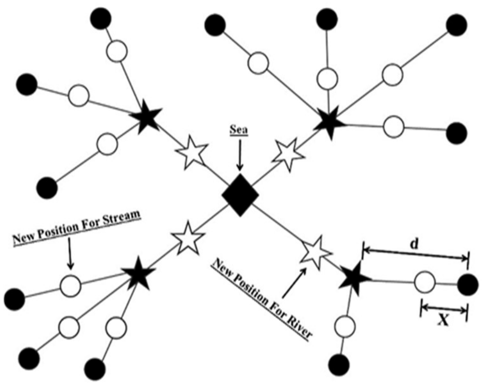

FIGURE 3. Schematic view for water cycle algorithm [29].

distributed number whether (uniformly or in an appropriate distribution) between 0 and (C × d). Enabling C > 1, streams are permitted to flow in various directions towards rivers. This concept can explain rivers flowing into the ocean. Therefore, the new position for streams and rivers can be obtained as follows:

$$X^{i+1}_{stream} = X^{i}_{stream} + rand \times C \times (X^{i}_{River-} X^{i}_{stream}) \quad (26)$$

$$X^{i+1}_{River} = X^{i}_{River} + rand \times C \times (X^{i}_{Sea-} X^{i}_{River}) \quad (27)$$

where *rand* is a randomly distributed number in a uniform way between 0 and 1. If the solution obtained by a stream is better than its linking river, the positions of river and stream are swapped (i.e., stream becomes river and river becomes stream). Figures 3-5 show the algorithm schematic diagrams and the flow chart of the WCA.

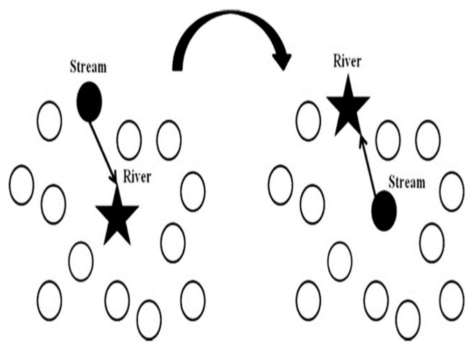

FIGURE 4. The position of the stream (raindrop) and the river replacement [29].

The star is the river and the black circle is the best among other streams. The procedure of the water cycle optimization technique is as shown in Figure 5.

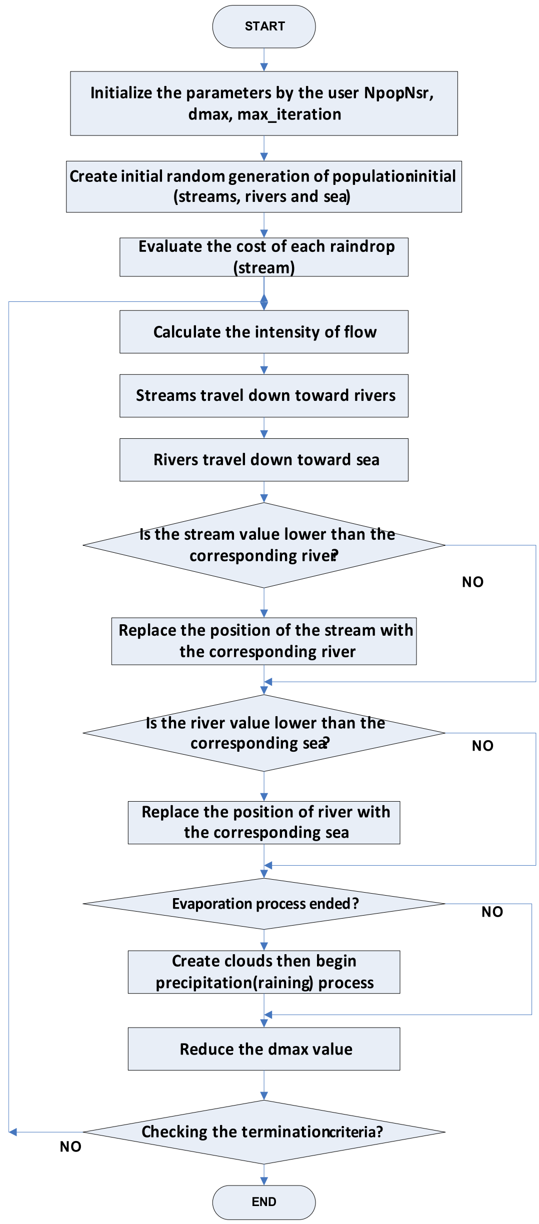

FIGURE 5. A flowchart for water cycle optimization algorithm.

V. SIMULATION AND RESULTS

The two algorithms (GSA and WCA) are implemented using MATLAB®and are used to find the optimal weekly generation dispatch of the two systems described in Section III.

This sections presents the results with special focus on identifying:

- the effect of integrating PHEVs with the wind/solar sources
- The effect of weekly load profile variability...
- The difference between the performance of WCA and GSA as applied to the problem under investigation.

Tables 4 &5 show the results of unit commitment scheduling for a heavily loaded day (Tuesday) applying both WCA & GSA for the 3 generator test system.

In Tables 4&5, in any specific hour, if the sign of the PHEV is negative, that means the PHEV works as a load. Table 6 shows the comparison in both production and emission costs between GSA and WCA solvers for Tuesday.

Comparing the results obtained from Table 6 with the results from [3], the results show the superiority of

TABLE 4. The generation for tuesday applying WCA (peak load 100%).

Hour	DEMAND	Thermal Gen 1	Thermal Gen 2	Thermal Gen 3	Wind	Solar	PHEV
1	200	84.55	0	108.78	8.20	0	4.1
2	200	75.43	0	111.36	11.4	0	7.82
3	250	59.8	0	122.12	66.9	0	2.05
4	250	65.69	0	112.38	69.8	0	3.72
5	250	91.26	0	104.85	55.40	0	1.30
6	200	67.04	0	80.22	50.9	0	0.89
7	350	112.8	0	231.96	4.6	5	1.76
8	500	104.13	0	327.57	49.3	22.04	1.60
9	600	134.06	0	367.10	45.6	53.95	-2.79
10	800	325.63	0	399.33	10.10	67.4	-12.75
11	800	313.19	0	397.44	24.8	67.32	31.88
12	700	264.05	0	354.61	37.3	69.64	-15.94
13	750	237.79	0	392.99	59	65	6.38
14	750	225.58	0	395.71	78.1	58.27	8.63
15	700	214.78	0	389.93	44.9	53.79	10.8
16	650	205.68	0	382.97	19.5	47.06	5.13
17	500	156.93	0	336.09	3.7	27.11	10.61
18	600	192.95	0	381.16	16.5	11	8.58
19	600	146.04	0	383.77	72.2	0	5.9
20	700	233.86	0	395.74	73.3	0	14.0
21	650	200.81	0	388.82	65.3	0	14.74
22	550	151.44	0	378.34	24.5	0	16.81
23	450	107.55	0	331.68	8.2	0	4.09
24	350	59.70	0	284.08	11.4	0	7.82

GSA over WCA. The overall costs are11.2% less using the GSA algorithm.

The same observation can be made using a Sunday load profile (light loaded day), as shown in Table 6. Figures 6 and 7 show the share of each generation type in the production and emission costs for Sunday using WCA and GSA techniques.

Summing the costs over the entire week emphasizes the fact that GSA is superior to WCA in solving the multi-day unit commitment problem. The results over the whole week which contain all possibilities and uncertainties of the load and the renewable sources show that, the total production (emission) costs is 15.35% (12.08%) less compared to the WCA. The results are depicted in Figure 8 &9. The advantage of the study is to schedule the thermal and the renewable resources based on more realistic values. From Table 6 &7, Tuesday emission cost result is (3658 $) while Sunday emission cost is (1783$). If the assumption built on the same load of Tuesday over the whole week about 50% over price will be in the calculation of emission cost, or less by 50% if Sunday load value considered over the whole week. So, the real consideration of load profiles and system volatility will give an accurate insight for operator to take the right decisions. The only disadvantage is that can take a bit longer time than old techniques but with reliable solution.

The optimization algorithms tend to consume all the amount of energy supplied from renewable resources and

TABLE 5. The generation for tuesday applying GSA (peak load 100%).

Hour	DEMAND	Thermal Gen 1	Thermal Gen 2	Thermal Gen 3	Wind	Solar	PHEV
1	200	30.31	0	159.1	8.20	0	4.1
2	200	34.18	0	152.00	11.4	0	7.82
3	250	49.73	0	130.89	66.9	0	2.05
4	250	59.39	0	118.3	69.8	0	3.72
5	250	30.51	0	161.71	55.40	0	1.30
6	200	34.57	0	111.74	50.9	0	0.89
7	350	78.51	0	260.82	4.6	5	1.76
8	500	38.97	0	389.46	49.3	22.04	1.60
9	600	128.33	0	372.49	45.6	53.95	-2.79
10	800	324.88	0	400	10.10	67.4	-12.75
11	800	310.14	0	399.98	24.8	67.32	31.88
12	700	260.14	0	349.98	37.3	69.64	-15.94
13	750	240.59	0	386.91	59	65	6.38
14	750	215.79	0	399.24	78.1	58.27	8.63
15	700	202.61	0	399.99	44.9	53.79	10.8
16	650	216.5	0	368.74	19.5	47.06	5.13
17	500	166.5	0	318.74	3.7	27.11	10.61
18	600	173.54	0	399.98	16.5	11	8.58
19	600	128.42	0	400	72.2	0	5.9
20	700	246.89	0	381.33	73.3	0	14.0
21	650	207.48	0	378.35	65.3	0	14.74
22	550	157.48	0	368.63	24.5	0	16.81
23	450	107.48	0	318.63	8.2	0	4.09
24	350	57.48	0	268.63	11.4	0	7.82

TABLE 6. Production and emission costs (Tuesday) applying WCA and GSA for the three generator system.

Day	Production Cost WCA	Production Cost GSA	Emission Cost WCA	Emission Cost GSA
Tuesday	266814.00	239830.40	3658.33	3342.88

TABLE 7. Production and emission costs (Sunday) applying WCA and GSA.

Day	Production Cost WCA	Production Cost GSA	Emission Cost WCA	Emission Cost GSA
Sunday	243765.00	164326.80	2610.37	1783.07

TABLE 8. The generation for tuesday applying GSA.

Load/KW	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	Wind	Solar	PHEV
1025	0	330	0	343	0	144	0	210	0	87	8	0	4
1000	0	393	0	349	0	197	0	0	0	172	11	0	8
900	0	382	0	359	0	186	0	0	0	0	67	0	2
850	0	388	0	319	0	147	0	0	0	0	70	0	4
1025	0	394	0	269	0	159	0	0	275	0	55	0	1
1400	0	398	0	317	0	215	0	0	487	0	51	0	1
1970	0	407	0	432	0	362	258	258	624	0	5	5	2
2400	0	442	0	564	0	747	564	401	652	0	49	22	2
2850	0	395	172	480	0	355	529	361	614	0	46	54	-3
3150	0	375	358	423	229	231	567	369	832	0	10	67	-13
3300	0	365	583	396	255	190	615	331	783	0	25	67	32
3400	0	320	568	379	277	195	721	341	736	0	37	70	-16
3275	0	314	550	358	526	181	730	315	689	0	59	65	6
2950	0	366	555	373	630	137	0	271	767	0	78	58	9
2700	0	359	509	335	597	118	0	260	764	0	45	54	11
2550	0	361	479	408	0	69	0	249	739	199	20	47	5
2725	50	340	430	383	0	163	250	338	701	181	4	27	11
3200	0	330	469	334	248	135	464	372	756	155	17	11	9
3300	0	0	585	404	431	101	510	331	755	151	72	0	6
2900	0	0	557	378	0	147	614	319	777.6	110	73	0	14
2125	0	0	576	401	0	125	695	372	0	87	65	0	15
1650	0	0	0	399	0	97	671	362	0	160	25	0	17
1300	0	0	0	393	0	79	729	0	0	237	50	0	16
1150	100	0	0	351	0	127	608	0	0	0	40	0	14

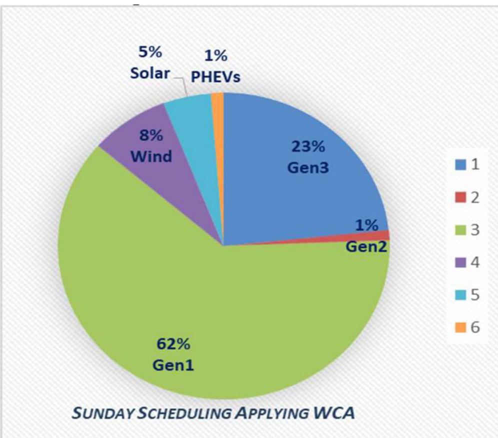

FIGURE 6. Pie chart applying WCA for Sunday Scheduling.

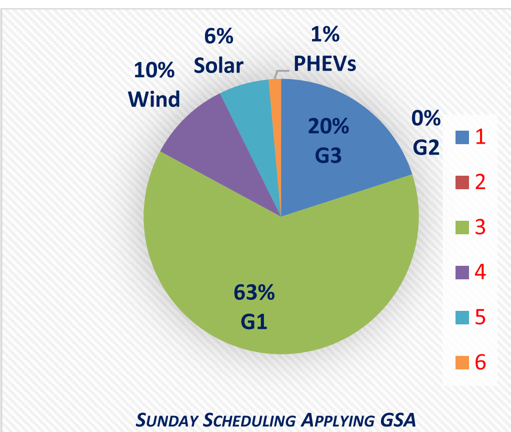

FIGURE 7. Pie chart applying GSA for Sunday Scheduling.

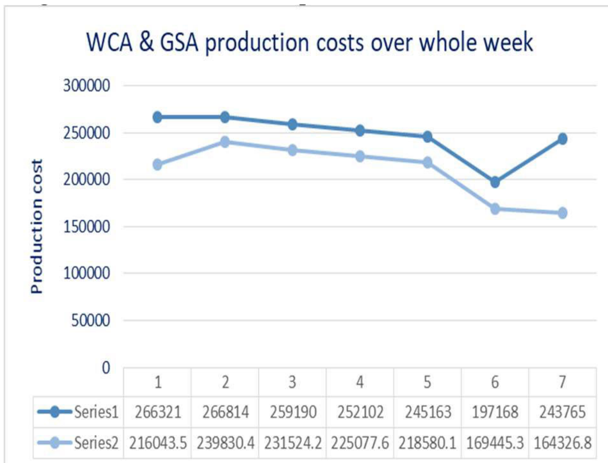

FIGURE 8. The production cost applying WCA & GSA over the whole week.

PHEVs. With the assumption of fixed profile for the Wind, Solar, and PHEVs, the energy served for each day almost the same. The effect of the day profiles is clear on Tuesday, the heavy loaded day, which is having the maximum reduction of emission cost because the optimizer tends to take the whole renewable resources energy. Some effect is distinguished on Sunday, the light load day, the optimal solution does not consume the whole offered renewable energy can be obtained, so the emission cost is at its minimum value.

To show the ability of the GSA to handle larger systems, the algorithm is used to produce the weekly generation schedule of the 10 generator unit data [30] as shown in Table 8.

One thing to note is the impact of PHEV charging/discharging effect on the thermal generation contribution. As it can be revealed from Table 8, if the PHEVs work properly, the most expensive thermal unit is not needed to share in the energy scheduling, e.g. generator 2 in the 3 unit system and generator 1 in the 10 unit system. If the PHEV

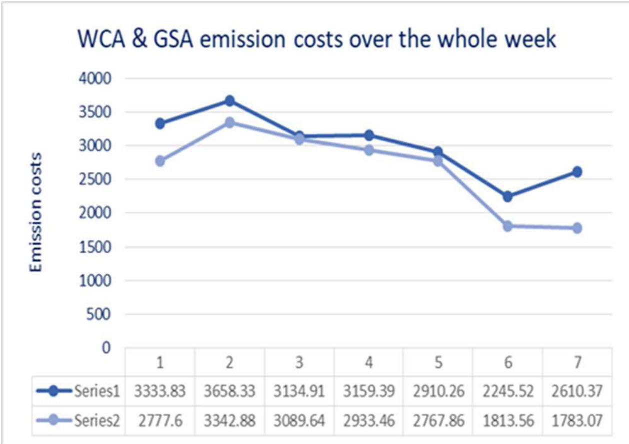

FIGURE 9. The emission cost applying WCA & GSA over the whole week.

operate as load, particularly during the system peak hours, the need for generators 2 in 3 unit system and generator 1 in 10 unit is vital to reduce both production and emission costs.

VI. CONCLUSION

This article introduced a comprehensive model for weekly generation scheduling of small scale systems taking into account (a) PHEV, (b) wind/solar resources intermittency, and (c) load variability. The model is formulated as an optimization problem together with its operating constraints. The optimized problem is then solved using two recent heuristic-based approaches, namely GSA and WCA algorithms. The results verify the novelty of the model and the GSA in taking the optimal scheduling decision to reduce the overall production and emission costs. The proposed model under study clinches some of the important points:

- Integrating RERs is an important approach to establish and guarantee the assessment of decarbonized system.
- Due to the volatility of the RERs behaviors, the PHEV can help in reducing the volatility of the RERs.
- In the time of PHEV acts as a load, the most expensive generator mostly integrated into the generation in return to smooth the generation profile.
- The Water Cycle Algorithm and Gravitational Search Algorithm are two promising techniques, but in the scheduling energy management, Gravitational Search Algorithm proves its prevailing performance over all week days and for 3 units and 10 unit systems.

REFERENCES

[1] T. Ribera and J. Sachs, "Pathways to deep decarbonization (2015 report)," DDPP, Tech. Rep., 2015.
[2] R. Swief, T. Abdel-Salam, and N. El-Amary, "Photovoltaic and wind turbine integration applying cuckoo search for probabilistic reliable optimal placement," *Energies*, vol. 11, no. 1, p. 139, Jan. 2018.
[3] H.-A. ElAzab, R. Swief, N. El-Amary, and H. Temraz, "Unit commitment towards decarbonized network facing fixed and stochastic resources applying water cycle optimization," *Energies*, vol. 11, no. 5, p. 1140, May 2018.
[4] R. A. Swief and N. H. El-Amary, "Optimal probabilistic reliable hybrid allocation for system reconfiguration applying WT/PV and reclosures," *Ain Shams Eng. J.*, vol. 11, no. 1, pp. 109–118, Mar. 2020.
[5] R. A. Swief and M. M. El-Din, "Combining both plug-in vehicles and renewable energy resources for unit commitment studies in smart grid," *IOSR J. Electr. Electron. Eng.*, vol. 8, no. 3, pp. 01–08, 2013.
[6] H. Morais, T. Sousa, J. Soares, P. Faria, and Z. Vale, "Distributed energy resources management using plug-in hybrid electric vehicles as a fuel-shifting demand response resource," *Energy Convers. Manage.*, vol. 97, pp. 78–93, Jun. 2015, doi: 10.1016/j.enconman.2015.03.018.
[7] K. Li, Y. Xue, S. Cui, Q. Niu, Z. Yang, and P. Luk, "Advanced computational methods in energy, power, electric vehicles and their integration," in *Proc. Int. Conf. Life Syst. Modeling Simulation (LSMS) Int. Conf. Intell. Comput. Sustain. Energy Environ. (ICSEE)*, vol. 1842. Berlin, Germany: Springer, Sep. 2017.
[8] R. A. Osama, A. Y. Abdelaziz, R. Swief, M. Ezzat, and A. F. Zobaa, "A probabilistic approach for maximizing the islanding success of microgrids," in *Proc. 19th Int. Middle East Power Syst. Conf. (MEPCON)*, Dec. 2017, pp. 392–396.
[9] R. Swief, T. Abdel-Salam, and N. El-Amary, "Photovoltaic and wind turbine integration applying cuckoo search for probabilistic reliable optimal placement," *Energies*, vol. 11, no. 1, p. 139, Jan. 2018.
[10] R. A. Swief and N. H. El-Amary, "Optimal probabilistic reliable hybrid allocation for system reconfiguration applying WT/PV and reclosures," *Ain Shams Eng. J.*, vol. 11, no. 1, pp. 109–118, Mar. 2020.
[11] P. Makeen, R. Swief, T. Abdel-Salam, and N. El-Amary, "Smart hybrid micro-grid integration for optimal power sharing-based water cycle optimization technique," *Energies*, vol. 11, no. 5, p. 1083, Apr. 2018, doi: 10.3390/en11051083.
[12] X. Yang, J. Long, P. Liu, X. Zhang, and X. Liu, "Optimal scheduling of microgrid with distributed power based on water cycle algorithm," *Energies*, vol. 11, no. 9, p. 2381, Sep. 2018, doi: 10.3390/en11092381.
[13] H.-A. ElAzab, R. Swief, N. El-Amary, and H. Temraz, "Unit commitment towards decarbonized network facing fixed and stochastic resources applying water cycle optimization," *Energies*, vol. 11, no. 5, p. 1140, May 2018, doi: 10.3390/en11051140.
[14] H. Rezk, A. Fathy, A. A. Z. Diab, and M. Al-Dhaifallah, "The application of water cycle optimization algorithm for optimal placement of wind turbines in wind farms," *Energies*, vol. 12, no. 22, p. 4335, Nov. 2019, doi: 10.3390/en12224335.
[15] A. M. Ibrahim and R. A. Swief, "Comparison of modern heuristic algorithms for loss reduction in power distribution network equipped with renewable energy resources," *Ain Shams Eng. J.*, vol. 9, no. 4, pp. 3347–3358, Dec. 2018.
[16] T. Niknam, M. R. Narimani, R. Azizipanah-Abarghooee, and B. Bahmani-Firouzi, "Multiobjective optimal reactive power dispatch and voltage control: A new opposition-based self-adaptive modified gravitational," *IEEE Syst. J.*, vol. 7, no. 4, pp. 742–753, Dec. 2013.
[17] K. Pal, C. Saha, S. Das, and C. A. Coello Coello, "Dynamic constrained optimization with offspring repair based gravitational search algorithm," in *Proc. IEEE Congr. Evol. Comput.*, Jun. 2013, pp. 2414–2421.
[18] A. A. Ibrahim, A. Mohamed, and H. Shareef, "Power quality monitor placement method using adaptive quantum-inspired binary gravitational search algorithm," in *Proc. 10th Int. Power Energy Conf. (IPEC)*, Nov. 2012, pp. 363–368.
[19] M. Doraghinejad, H. Nezamabadi-pour, A. Hashempour Sadeghian, and M. Maghfoori, "A hybrid algorithm based on gravitational search algorithm for unimodal optimization," in *Proc. 2nd Int. eConf. Comput. Knowl. Eng. (ICCKE)*, Oct. 2012, pp. 129–132.
[20] S. E. Farsangi, E. Rashedi, and M. M. Farsangi, "Multi-objective VAr planning using fuzzy-GSA," in *Proc. 2nd Conf. Swarm Intell. Evol. Comput. (CSIEC)*, Mar. 2017, pp. 147–151.
[21] A. Ghasemi, S. S. Mortazavi, and E. Mashhour, "Hourly demand response and battery energy storage for imbalance reduction of smart distribution company embedded with electric vehicles and wind farms," *Renew. Energy*, vol. 85, pp. 124–136, Jan. 2016, doi: 10.1016/j.renene.2015.06.018.
[22] G. A. A. Brigatto, C. C. B. Carmargo, and E. T. Sica, "Multiobjective optimization of distributed generation portfolio insertion strategies," in *Proc. IEEE/PES Transmiss. Distrib. Conf. Expo., Latin Amer. (TD-LA)*, Nov. 2010, pp. 622–628.
[23] World Bank and Ecofys. (2017). *Carbon Pricing Watch 2017*. Accessed: Mar. 3, 2018. [Online]. Available: https://openknowledge.worldbank.org/handle/10986/26565
[24] A. M. Elsayed, A. M. Maklad, and S. M. Farrag, "A new priority list unit commitment method for large-scale power systems," in *Proc. 19th Int. Middle East Power Syst. Conf. (MEPCON)*, Dec. 2017, pp. 359–367.

[25] A. Y. Saber and G. K. Venayagamoorthy, "Efficient utilization of renewable energy sources by gridable vehicles in cyber-physical energy systems," *IEEE Syst. J.*, vol. 4, no. 3, pp. 285–294, Sep. 2010.
[26] A. Y. Saber and G. K. Venayagamoorthy, "Plug-in vehicles and renewable energy sources for cost and emission reductions," *IEEE Trans. Ind. Electron.*, vol. 58, no. 4, pp. 1229–1238, Apr. 2011.
[27] H. M. Al Ghaithi, G. P. Fotis, and V. Vita, "Techno-economic assessment of hybrid energy off-grid system—A case study for masirah island in oman," *Int. J. Power Energy Res.*, vol. 1, no. 2, pp. 103–116, Jul. 2017, doi: 10.22606/ijper.2017.12003.
[28] J. Shi, X. Dong, T. Zhao, Y. Du, H. Liu, Z. Wang, D. Zhu, D. Ji, C. Xiong, and L. Jiang, "The water cycle observation mission (WCOM): Overview," in *Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS)*, Beijing, China, Jul. 2016, pp. 3430–3433.
[29] O. Bozorg-Haddad, M. Solgi, and H. A. Loáiciga, *Meta-Heuristic and Evolutionary Algorithms for Engineering Optimization*, 1st ed. Hoboken, NJ, USA: Wiley, 2017, pp. 231–240.
[30] A. H. Rashed, E. N. Abdallah, and F. Benhamida, "A hopfield neural network based dynamic dispatch solver," in *Proc. 10th Int. Middle East Power Syst. Conf. (MEPCON)*, vol. 5, Dec. 2005, pp. 515–525.
[31] World Bank and Ecofys. (2017). *Carbon Pricing Watch 2017*. [Online]. Available: https://openknowledge.worldbank.org/handle/10986/26565

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