Coronavirus Herd Immunity Optimizer (CHIO) for Transmission Expansion Planning

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***Abstract*— This paper presents a novel mathematical model to simultaneously tackle the economic dispatch (ED) problem considering valve point effect, load uncertainty, distributed generation (DG) uncertainty, incentive-based demand response, and plug-in electric vehicle into the transmission expansion planning (TEP) problem to minimize the total cost of the system. Monte–Carlo is employed to consider the uncertain characteristic of DGs and loads. Considering ED problem in solving TEP problem with uncertain aspects of DGs and loads, made the problem so complicated. So, to overcome this complicity, a new meta-heuristic coronavirus herd immunity optimizer (CHIO) algorithm is utilized. The presented methodology is verified on an IEEE 24-bus test system. Finally, to evaluate the CHIO algorithm efficiency, a comparison is made between the results obtained by CHIO and Branch and Bound (B&B) algorithm. Numerical results show the efficiency of the newly presented methodology in solving TEP and ED problems simultaneously.**

Keywords— Transmission Expansion Planning, CHIO algorithm, Demand response, economic dispatch, plugin- electric vehicles, uncertainty.

NOMENCLATURE

A_i^j	Incentive price of demand response programs paid to the consumer in *j*th load period (US $/MW)
a_i,b_i,c_i,e_i and f_i	Cost coefficient of the *i*th generator
C_{ij}	Cost of a new lines that can be added to the *i-j* right-of-way
C_{DG}	Cost of DG generation
C_{DR}	Cost of incentive-based demand response participation (US $)
C_{Gen}	Generation cost for thermal generators
C_{PEV}	Cost of the electrical vehicles
d_i	Demand in each load bus
$d_i^{\min}, d_i^{\max}$	Maximum and minimum demand vectors at bus *i*
d_i^j and d_{0i}^j	Initial load demand value and new load demand value at bus *i* for the *j*th load level (MW)
E_i^j	Elasticity of the *j*th load level with respect to *i*th bus
$E_i\,(P_{Geni}^j)$	Valve point loading effect of the *i*th unit
F_{ik}^j	Total power flow in the i_k circuit for the *j*th load level (MW)
L_d	Number of load levels
N_l	Number of circuits connected to bus *j*
n_{ik}^o and n_{ik}^j	Number of circuits in base case and new circuits added the *j*th load to the i_k line
$n_{ik}^{\max}$	Maximum number of circuits that can be added to the i_k right-of-way
$N_{PEV}^{\max}$	Maximum number of PEVs
N_{GEN}, N_{PEV} and N_{DG}	Number of thermal generators, PEVs, and distributed generation farms
P_{DGi}^j	Scheduled distributed generation power from the *i*th distributed generation at load level *j* (MW)
P_{dk}^j	Active load at bus k for load level *j* (MW)
P_{Geni}^j	Active power generation at the *i*th bus at load level *j* (MW)
$p_{Geni}^{\max}$ *and* $p_{Geni}^{\min}$	Minimum and maximum active power generation at the *i*th bus (MW)
$P_{PEV_i}^j$	Power generated by the electric vehicle connected to bus *i* at load level *j* (MW)
pen_i^j	Penalty at bus *i* for the *j*th load level (US $/MW)
v	Fitness function
β andα	Penalty parameters
ρ_{0i}^j and ρ_i^j	Original electricity prices and spot electricity prices at bus *i* for the *j*th load (US $/MW h) level (US $/MW h)

θ_m^j and θ_n^j	Phase angle at buses *m* and *n* for load level *j* (rad)
γ_{ik}	Susceptance of a line among buses *i* _ *k*

I. INTRODUCTION

Transmission expansion planning (TEP) is one of the essential sectors of long-term power system planning. The objective of TEP problems is to determine where, when and how many new lines should be installed in the system so that the system could supply the forecasted load over a given time horizon [1]. Usually, the load demand is taken into consideration as a major source of uncertainty that requires special attention. In the most previous planning studies, the uncertainty in demand has not been taken into account [2]. In other words, the TEP plan is only solved for one distribution profile of demand which can also bring about an expansion plan that violates various technical and fiscal constraints.

The other factor that should be considered in the TEP problem is the economic dispatch (ED). The specific purpose of ED is to distribute power demand among planned generators at the lowest cost while satisfying all the system and generator constraints. So, TEP can be used to correct the base generation planning plans. Therefore, generation and transmission planning problems should be made on the basis of decomposition and coordination to optimize the overall power system planning [3].

In addition to the demand growth and global warming, the concerns about depletion time of fossil resources which is estimated to take place before 2025, has motivated many industries to focus on renewable energy resources (RES). On the other hand, quoted from the electric power research institute (EPRI) report, it is expected in the U.S by 2020 up to 35% of the total vehicles will be plugin electric vehicles (PEVs) [4]. PEVs can be used in the new grid equipment namely grid-to-vehicle (G2V) and vehicle-to-grid (V2G), if the plugin electrical vehicles are seen as controlled loads (G2V). In such siuation, the battery is charged by the network (G2V) or support the grid (V2G) by injecting the power stored in battery back into the network [5].Published research works show that distributed generation (DG) as a local generation and PEVs as a portable power plant, decrease investment and operation costs. However, due to the limitations of traditional power systems and the randomness and intermittence characteristic of DGs, modern power system planning studies face further uncertainty of the nodal power injections arising from the emergence of DGs. Hence, it is necessary to take the recent developments in the electricity industry, including the increasing growth of DGs and PEVs into account.

Nevertheless, due to the intermittencies of RES, demand response (DR) may be considered as a means to facilitate the use of RESs to enhance the flexibility of a system by re-shaping the system load profile [6]. With the expansion of DR programs, customers can affect the system operation. As customer engagement increases, power system planning models naturally need to be revised and modified. Generally, DR programs are categorized into incentive-based (IBDR) and price-based (PBDR) programs. In PBDR, the customer energy usage is modified according to the fluctuations in electricity prices that are notified by ISO, while in IBDR programs, specified rewards (as the main tool) are used to modify consumer energy demand. More details can be found in [7].

Several research works deal with generation expansion planning (GEP) and TEP in conventional power systems [8-10]. A multi-objective multi-period TEP-GEP model considering RES and IBDR is discussed in [11]. It indicates that the execution of DR program in the planning procedure results in decreasing in power generation capacity, emissions, and the planning costs of the system. A scenario-based robust static TEP is proposed in [12]. The proposed framework considers transmission losses, N-1 security criteria, and uncertainties over wind power generation. The TEP problem is modeled as a mixed-integer nonlinear programming problem. The bi-level formulation is used to solve the TEP problem.

High penetration of various types of RES and their generation uncertainties, in the composite GEP-TEP of the IRAN power grid, is investigated in [13]. It also considers environmental and economic constraints and reliability criteria in its formulation. In [14] a co-optimization approach is utilized for GEP and TEP, which determines the optimal placement and size of solar PVs. A two-stage optimization method is introduced for TEP in a large-scale network with high penetration of RES in [14]. It uses an enhanced Benders' decomposition approach to deal with the optimization problem.

This paper proposes a mathematical model to include the ED in TEP problem and also solve it by considering the PEV, DG, DR programs along with uncertainties raised from both load and RES output. Uncertainty in each load bus individually is considered as a term in the proposed model. Also, to deal with the DG generation uncertainties, a probabilistic analysis tool, i.e. the Monte–Carlo simulation (MCS) method is used to simulate a large number of feasible generation scenarios considering DG output probability density functions (PDFs) as well as the correlation between DG outputs. On the other hand, DG generation uncertainty can introduce tremendous difficulties for energy management in power systems. To mitigate such difficulties, IBDR program is used which can adjust the loads to adapt to the generation sources. However, the implementation of DR programs for generation companies entails costs that are due to changes in electricity and grid load tariffs in the IBDR programs and should be incorporated into the original TEP objective function. The coronavirus herd immunity optimizer (CHIO) which is modeled for continuous optimization, is used to solve this complex optimization problem in order to acheive better solutions, performance, and computational time. The effectiveness of the suggested algorithm has been compared with Branch and Bound (B&B) algorithm. Finally, to assess the capabilities of the presented model, the modified IEEE-24 bus is used as a test system. As a whole, the main contributions of this paper can be listed as follows:

- Development of a mathematical formulation for involving DG, EV, and IBDR as energy sources in TEP problem aiming at decreasing investment costs,
- Considering the load and DG uncertainties in TEP problem,
- Investigate the importance of integrating ED and IBDR programs into the new proposed mathematical investment model.

The rest of the paper is organized as follows. Section II puts forward the proposed formulation. In Section III, the IEEE 24- bus test system and the obtained results from simulations are presented to confirm the efficiency of the proposed mathematical model. Finally, some relevant conclusions are discussed in Section IV.

II. Problem Formulation

In the first section, the DC-based TEP problem is modeled. Details of the DC model and its advantages and disadvantages in TEP problem are given in [15]. The objective function of the proposed mathematical model expressed by minimizing the sum of the investment and the operating costs as follows:

$$\min \quad v = \sum_{ik \in \Omega} c_{ik} n_{ik} + \sum_{i}^{L_d} C_{DRi} - \alpha \sum d_i + \beta \left\{ \sum_{j}^{L_d} \cdot \left[\sum_{i}^{N_{Gen}} C^{j}_{Geni} + \sum_{i}^{N_{DG}} C^{j}_{DG_i} + \sum_{i}^{N_{PEV}} C^{j}_{PEV_i} \right] \right\} \tag{1}$$

In this formulation, the first term $c_{ik} n_{ij}$ represents the cost of a new transmission line. The second term is the cost of the *j*th load level of DR program which can be calculated as (2) [7]. Indeed, this cost is equal to the changes in the revenue of generation companies with the implementation of IBDR programs.

$$C_{DRj} = A_i^j \times \left(d^{j}_{0_i} - d_i^j \right) \tag{2}$$

where d_i^j is the consumer's consumption and can be calculated as:

$$d_i^j = d_{0i}^j \times \left[1 + \frac{E_i^j \times \left(\rho_i^j - \rho_{0i}^j + A_i^j + pen_i^j \right)}{\rho_{0i}^j} \right] \tag{3}$$

and E_i^j is cross-elasticity and defined as:

$$E_i^j = \frac{\partial d(i)}{\partial \rho(j)} \cdot \frac{\rho_0(j)}{d_0(i)} \tag{4}$$

The third term of (1) is the mathematical model for demand uncertainty of each load bus individually, and the demand in each load bus inside the $\left[d_i^{\min}; d_i^{\max} \right]$ interval. The fourth term of (1) represents the ED problem in the proposed TEP formulation. C^j_{Geni} is the generation cost for thermal generators. By considering the valve point effect as an operational constraint of thermal generator units, the thermal generation cost can be represented as (5) [16].

$$C^j_{Geni} = C_i (P^j_{Geni}) + E_i (P^j_{Geni}) \tag{5}$$

where $C_i (P^j_{Geni})$ and $E_i (P^j_{Geni})$ are the generation cost and valve point loading effect of the *i*th unit, respectively, that are given by (6)-(7).

$$C_i (P^j_{Geni}) = a_i (P^j_{Geni})^2 + b_i P^j_{Geni} + c_i \tag{6}$$

$$E_i (P^j_{Geni}) = \left\{ e_i \sin\left[f_i (P^{\min}_{Geni} - P^j_{Geni}) \right] \right\} \tag{7}$$

The fifth term of (1) represents the cost function of DG power. It must be noted that the cost related to DGs which not belong to the main grid, is not considered in the fifth term of (1).

Eventually, the last term of (1) gives the cost of the PEVs. The PEV owners may set the charging and discharging time of their vehicles based on the spot electricity price to get more benefits. The power cost of the PEVs is calculated by (8) [17]:

$$C^j_{PEV_i} = P^j_{PEV_i} \cdot \rho_i^j \tag{8}$$

A. Problem Constraints

To solve the optimization problem, the following constraints have to be regarded:

During peak load periods, PEVs act as a power source ($+\sum P_{PEVi}$), and during other periods, they are considered as a load ($-\sum P_{PEVi}$). Hence, the conservation of power in each node represented as:

$$\sum F_i^j + \sum P^j_{DGi} + \sum P^j_{Geni} \pm \sum P^j_{PEVi} - P^j_{dk} = 0, \quad \forall i \in N_{lk} \tag{9}$$

Equation (10) shows the power flow related to each bus which must be respected in whole planning horizon.

$$F_{ik}^j = \gamma_{ik} \left(n^o_{ik} + n^j_{ik} \right) \left(\theta^j_m - \theta^j_n \right), \quad n \neq m, \ \forall n, m \in N_b \tag{10}$$

The maximum active power flow limits for each transmission line, represented by (11), should be respected to maintain network stability.

$$\sum_{\forall i \in N_{lk}} | F_i^j | \leq \left(n_i^o + n_i^j \right) F_i^{\max} \tag{11}$$

The power generation and DG limits at each bus should be remain in their acceptable range as follows:

$$0 \leq P^j_{DGi} \leq P_{DGri} \tag{12}$$

$$p^{\min}_{Geni} \leq p^j_{Geni} \leq p^{\max}_{Geni} \tag{13}$$

The forecasted or pre-registered available number of PEVs should be equal to or less than the maximum number of PEVs for the planning of the desired period. So, the vehicle balance constraint in TEP problem is stated as

$$\sum_{t=1}^{hr} N_{PEV}(t) \leq N^{\max}_{PEV} \tag{14}$$

The expansion of new lines for each branch should be under the following constraint:

$$0 \leq n^j_{ik} \leq n^{\max}_{ik} \tag{15}$$

The considered assumptions in this paper are as follows:

- The TEP problem is solved for a 100% load level period,
- The group of DGs and PEVs are installed on specific locations,
- The maximum and minimum power which is saved through the PEV is assumed to be 90% and 20% of its maximum power, respectively,
- The DG units will not participate in the generation/consumption of reactive power,
- A maximum of 3 parallel lines assumed to be added in each possible path,
- The minimum value of P_{Geni} is 0 MW.

III. Simulation Results and Discussion

To explain the proposed model, static planning is considered and implemented in MATLAB environment. In [18] a new nature-inspired human-based optimization algorithm named CHIO is introduced. In this paper, the CHIO algorithm has been implemented to solve the examined TEP

TABLE I. SIX-UNIT GENERATOR CHARACTERISTICS [16]

Unit	Maximum. generation (MW)	a_i (\$/(MW)^2 h)	b_i (\$/MWh)	c_i (\$/h)	e_i (\$/h)	f_i (rad/MW)
1	80.0	0.1090	39.580	950.6060	25.0	0.0178
2	130.0	0.1211	39.510	800.7050	30.0	0.0168
3	240.0	0.1058	46.159	451.3250	20.0	0.0163
4	300.0	0.0354	38.305	1243.5310	20.0	0.0152
5	340.0	0.0280	40.396	1049.9980	30.0	0.0128
6	470.0	0.0211	36.32	1658.5690	60.0	0.0136

TABLE II. DEMAND RESPONSE PROGRAM DATA [17]

Load Levels	1	2	3	4	5	6	7	8	9	10
Percentage Of Base Load (%)	100	90	80	70	60	50	60	50	40	30
Hour	400	500	600	800	800	1000	1000	1200	1200	1260
Electricity	-0.10	-0.09	-0.085	-0.08	-0.075	-0.08	-0.075	-0.06	-0.05	-0.03
Spot Electricity Price	32.0	30.0	28.0	26.0	25.0	26.0	25.0	24.0	23.0	22.0
Incentive Price	16.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

problem, and the obtained results are compared to those of B&B algorithm. The IEEE 24-bus system is utilized as a test system to validate the proposed model. This network consists of 8550 MW of load demand, 34 existing branches, 7 new candidate lines, 24 buses and 41 possible right-way paths. The system data is available in [19]. Details of DRP data are shown in Table I. In order to investigate the proposed TEP formulation, seven cases are investigated as follows:

1) *Case 1:* This case is considered as a base case in which the TEP problem is supposed to be solved only for the given load and generation plan.

2) *Case 2:* The effect of considering DGs with their generation uncertainties in the TEP problem is investigated in this case. For modeling the DGs, solar panels with a total nominal power of 400 MVA are considered (5% of the total load connected), which have 10% oscillation, depending on the intensity of sunlight. The group DGs are installed on bus 11.

3) *Case 3:* TEP with considering 5% uncertainty in demand individually for each load bus is considered as the third case.

4) Case 4: The impact of considering the ED in TEP problem has been studied in this case. The power output of generating units can change among their minimum and maximum limits.

5) *Case 5:* The fifth case shows the impact of the IBDR program on reducing the total cost of the TEP plan. In order to perform the DR program at the varying load levels, the period of 8760 hours is selected, as recommended in [20]. Spot electricity price and the elasticity price of each load level are taken from [21]. Spot electricity price, elasticity, and penalty price offered to the consumers for *j*th load level at *i*th bus are the same. The info on the DR program is given in Table II.

6) *Case 6:* The integration of PEVs at a load bus is investigated in this case. The maximum number of PEVs considered to be 500,000 and they are installed on bus 8. The PEVs parameters considered as: maximum battery capacity = 25 kWh, minimum battery capacity = 10 kWh, average battery capacity = 15 kWh and inverter efficiency = 85% [22].

7) *Case 7:* In this case, the impact of all parameters (presented in Case 2 to Case 6) are considered simultaneously.

Numerical results and ED for all cases of the TEP problem are shown in Table. III and IV. According to Table IV, for the base case, B&B algorithm suggests installing one line between buses 1-5 and 2-3, two lines between buses 16-17 and 6-10 and also three lines between buses 20-23 and 1-2 (totally 15 new lines). The total cost for the implementation of this plan is 398.3 million dollars. In this case, CHIO algorithm presents a plan with 13 new lines, one line between buses 16-19, two lines between buses 3-9, 17-18, and 1-5 and also three lines between buses 4-9 and 7-8, which resulted in 389.9 million dollars investment cost.

TABLE III. ECONOMIC DISPATCH FOR ALL CASES OF THE TEP PROBLEM

Cases	Algorithm	P_{Gen1}	P_{Gen2}	P_{Gen7}	P_{Gen13}	P_{Gen15}	P_{Gen16}	P_{Gen18}	P_{Gen21}	P_{Gen22}	P_{Gen23}	P_{DG}	P_{PEV}	Total load at level 1 (MW)	Total generation (MW)
Case 1	-	576.0	576.0	900.0	1773.0	645.0	465.0	1200.0	1200.0	900.0	315.0	-	-	8550.0	8550.0
Case 2	B&B	531.7	531.7	558.2	1772.9	644.1	461.2	985.0	989.0	592.2	1114.0	370.0	-	8550.0	8550.0
	CHIO	570.1	570.1	750.3	1655.0	570.9	396.1	1189.3	1178.8	554.8	750.5	364.1	-	8550.0	8550.0
	B&B	490.8	568.2	894.5	1700.5	601.2	419.3	820.5	824.3	690.5	1540.2	-	-	8550.0	8550.0

Case 3	CHIO	522.1	520.5	825.6	1698.2	579.2	435.6	1075.2	861.9	589.5	1442.2	-	-	8550.0	8550.0
Case 4	B&B	468.2	571.9	899.4	1551.0	592.5	382.2	945.6	1189.3	384.1	1565.8	-	-	8550.0	8550.0
	CHIO	535.6	559.8	722.0	1554.3	598.3	388.0	1150.6	1090.2	693.6	1257.6	-	-	8550.0	8550.0
Case 5	B&B	576.0	568.2	755.2	1773.0	644.1	400.9	1200.0	1111.6	450.1	722.8	-	-	8201.9	8201.9
	CHIO	487.5	522.5	755.5	1668.9	642.1	441.5	955.1	951.4	536.1	1241.3	-	-	8201.9	8201.9
Case 6	B&B	575.2	576.0	898.1	1773.0	587.9	419.00	1189.3	1200.0	263.1	733.0	-	334.6	8549.2	8550.0
	CHIO	570.3	568.5	900.0	1771.2	612.6	460.2	986.1	985.2	186.8	1173.4	-	334.9	8549.2	8550.0
Case 7	B&B	469.3	530.1	794.6	1551.0	643.5	448.7	650.5	735.3	590.2	1087.5	449.8	251.4	8201.9	8201.9
	CHIO	470.5	542.8	748.5	1559.6	641.8	437.8	1200.0	756.2	175.3	960.6	450.1	258.7	8201.9	8201.9

TABLE IV. EPANSION PLANS FOR ALL CASES OF THE PROPOSED TEP PROBLEM

Cases	Algorithm	Total cost (10^6 U$)	Total new lines	New lines
Case 1	B&B	398.3	15	$n_{1-5}=1$, $n_{2-3}=1$, $n_{16-17}=2$, $n_{15-16}=3$, $n_{20-23}=3$,$n_{6-10}=2$, $n_{1-2}=3$
	CHIO	389.9	13	$n_{16-19}=1$, $n_{3-9}=2$, $n_{17-18}=2$, $n_{1-5}=2$, $n_{4-9}=3$, $n_{7-8}=3$
Case 2	B&B	350.5	12	$n_{2-4}=3$, $n_{6-10}=3$, $n_{1-5}=3$, $n_{17-18}=3$
	CHIO	342.2	11	$n_{3-9}=1$, $n_{1-2}=2$, $n_{7-8}=2$, $n_{16-19}=3$, $n_{4-9}=3$
Case 3	B&B	290.8	7	$n_{1-5}=1$, $n_{1-2}=3$, $n_{15-16}=3$
	CHIO	281.0	7	$n_{1-2}=1$, $n_{3-9}=1$, $n_{6-10}=2$, $n_{2-4}=3$
Case 4	B&B	155.5	6	$n_{20-23}=1$, $n_{3-9}=1$, $n_{5-10}=2$, $n_{7-8}=2$
	CHIO	149.4	7	$n_{6-10}=1$, $n_{1-5}=3$, $n_{4-9}=3$
Case 5	B&B	137.1	5	$n_{4-9}=1$, $n_{11-13}=1$, $n_{5-10}=1$, $n_{16-19}=2$
	CHIO	132.0	5	$n_{17-18}=2$, $n_{20-23}=3$
Case 6	B&B	130.3	3	$n_{3-24}=1$, $n_{6-10}=2$
	CHIO	130.3	3	$n_{16-19}=3$
Case 7	B&B	96.8	3	$n_{16-19}=1$, $n_{1-18}=2$
	CHIO	91.6	3	$n_{1-5}=1$, $n_{6-10}=1$, $n_{15-16}=1$

So, CHIO algorithm reaches a plan with fewer installed lines and investment cost in comparison with B&B algorithm. As it can be seen from Table IV, in all cases except Case 2, the number of new lines proposed by CHIO is less than or equal to the ones proposed by B&B. In Case 2, although the number of new lines proposed by CHIO is more than B&B, the investment cost of the presented plan by CHIO is less than B&B. This shows the investment cost of a plan is not only affected by the number of new lines, but also by their locations.

In Cases, 2 to 6, the effect of the different considered scenarios on reducing the total cost of the TEP program is investigated. As shown in Table III, with using B&B algorithm as an optimization method for the proposed method, Cases 2-6 have resulted in 27, 60.9, 65.6, and 67.3 percent reduction in the final cost compared to Case 1, respectively, and using the CHIO algorithm, Cases 2-6 have resulted in 28, 61.7, 66.1and 66.6 percentage reduction in the final cost w.r.t Case 1, respectively.

Finally, Case 7 simultaneously examines all the considered scenarios on the results of the TEP Program. According to Table III, using the B&B algorithm results in the construction of 3 new lines with a total cost of 96.8 (10^6 US $) but the CHIO algorithm results in the construction of 3 new lines with 91.6 (10^6 US $). Therefore, it can be concluded that the CHIO algorithm has achieved a better plan than the B&B method by establishing a suitable fit between different objective functions.

To expose the convergence overall performance of CHIO and B&B algorithms, a graph is plotted for case 7 in Fig. 1. As shown in Fig. 1, the CHIO algorithm reaches the optimal plan in 43 iterations while B&B algorithm takes 66 iterations.

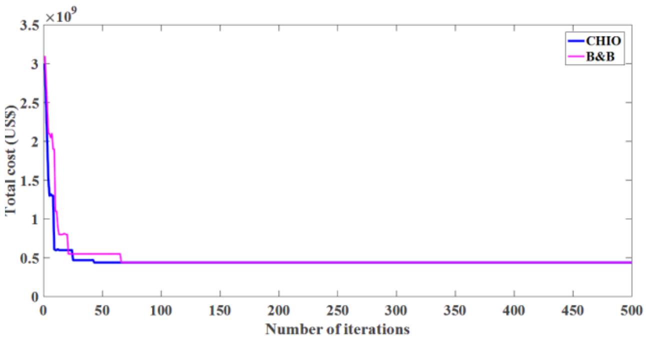

Fig. 1. Charging/discharging points of PEVs for the final case

Charging/discharging points of PEVs for the final case are shown in Fig. 2. At levels, 1-4 and 6 PEVs are charging and at the rest of the levels, PEVs are discharging.

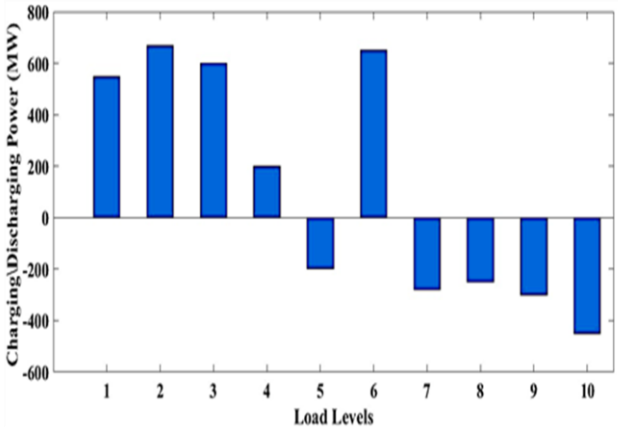

Fig. 2. Charging/discharging points of PEVs for the final case

IV. Conclusion

The increasing penetration of DGs and plug-in electric vehicles in power systems has caused the emergence of new challenges which in turn affects the TEP problem. This paper proposed an efficient method for TEP on which load uncertainty, uncertain behavior of DGs, plug-in electric vehicle, and incentive-based demand response program were tackled into the TEP problem formulation. In this way, the MCS was used to manage the uncertainties associated with the penetration of the DGs. To solve the constructed non-linear and non-convex optimization problem, a new meta-heuristic coronavirus herd immunity optimizer (CHIO) algorithm was utilized to solve this complex TEP problem. Also, evaluation among CHIO and B&B algorithms was presented to show the better performance of CHIO algorithm in solving TEP issues. The efficiency of the proposed model was tested on the IEEE 24-bus system in different cases.

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