A Genetic Algorithm for Battery-Based Energy Storage Transportation Using Railway

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Abstract

The use of renewable energy sources has increased significantly in the past few years. Due to the intermittent nature of the renewable energy sources, planning and distribution of this energy is considered a challenging process. Energy storage systems have a great potential towards these challenges as it can store energy from different sources and then distribute it to regions with high demand such as in the case of Battery Based Energy Storage System. In this paper, the impact of railway Battery Based Energy Storage System on the power grid is considered. A genetic algorithm is proposed for solving the dispatching of rechargeable battery-based energy storage train vehicles to satisfy the charging/discharging requirements of rural areas not directly connected to the power grid due to being temporary locations such as rural cities under construction and military rural campuses. A multi-objective model is proposed that has the following objectives: 1) to minimize the transportation cost associated with the train route; and 2) to minimize the number of Battery Storage vehicles. A Genetic Algorithm is developed and tested using numerical examples. The results show the effectiveness of the proposed algorithm in providing good solutions using the minimum number of Battery storage vehicles in a cost-effective energy distribution system.

1. Introduction

Energy has become a crucial element for sustainable development. Renewable energy, as an important source of energy, has been integrated in the power grid to provide a cleaner and more sustainable form of energy. The use of solar energy, wind energy, and other renewable energy power generation is gradually increasing. In this paper, the use of renewable energy is integrated in the electric power grid using Battery-Based energy Storage Systems (BBSS). This paper considers the use of railway network to transport the BBSS from the generators to areas with high demand or areas that are not linked with transmission lines. The BBSS stores energy from renewable energy sites and, by using the railway systems, transmits it to regions where such energy has the highest potential for grid management.

This is especially important in three cases: 1) the generating sites are too far away from the consumption sites and are already connected to railroads services; 2) the consumption sites are far away and not linked to the generating sites, but are connected to railroads services; and/or 3) the consumption (or generating) sites are dynamic with no fixed location, but accessible via the railroads. In other words, the problem is important when there is already a railroad network connecting the sites, meanwhile, the cost of connecting them to the same electric grids is high.

The paper is structured as follows. Section 2 discusses the literature related to the problem. Section 3 discusses the problem definition and the mathematical model for the problem. Section 4 introduces the proposed genetic algorithm. Section 5 shows the numerical experimentation conducted to test the effectiveness of the proposed model. Finally, section 6 summarizes the important findings and provides conclusions.

2. Literature Review

The energy distribution problem has attracted the research attention in the past few years. Xie et al. (2019) studied the impact of renewable energy on the power supply chain. They studied the power market and analyzed the different power supply chain operation modes. They discussed the optimal mode selection for renewable energy generator and power grid in different situations. Aflaki & Netessine (Aflaki & Netessine, 2017) analyzed the incentives for investing in the capacity to generate renewable electricity. They modeled the trade-off between renewable and nonrenewable from the investment cost, the nature of energy supply, fuel expenditures and carbon emission costs. They concluded that market liberalization may reduce investment in renewable capacity while increasing the overall system's cost and emissions; and that the intermittency of renewable technologies drives the effectiveness of carbon pricing mechanisms.

Kong et al. (2017) studied the capacity investment strategy under volatile electricity spot price when renewable energy penetration rate is low, taking into account whether the distributions of renewable energy source electricity and electricity spot price are independent or dependent. Kong et al. (2018) modeled the intermittence of wind power as uncertain supply, and develops a capacity-investment model under the uncertainties of both supply and demand. Their results show that optimal capacity investment is inversely related to priority dispatch elasticity. They also noticed that the profit from power generation is always higher when adopting the abandoned power management strategy. Fernando & Yahya (2015) studied the challenges of renewable energy management implementation and how firms manage the low carbon issue in their supply chains. Jiaping et al. (2017) studied the decisions on capacity investment for power producers facing a location problem in dual-echelon renewable energy source power supply chain. They assumed that demand and supply are uncertain, while the grid-connected power price is fixed. The problem was modeled as a Stackelberg game. They analyzed the impact of intermittence on profit distribution and risk sharing and compared between centralized and decentralized capacity investment decisions. They found that site candidates with higher market value should be given priority to invest under centralized decisions, while candidates with lower equivalent cost should be invested in first under conditions of a decentralized decision.

Sunar & Birge (2015) considered a day-ahead electricity market that consists of multiple competing renewable firms and conventional firms in a discrete-time setting. If a firm produces less than its cleared day-ahead commitment, the firm pays an undersupply penalty in proportion to its underproduction. The purpose of an undersupply penalty is to improve reliability by motivating each firm to commit to quantities it can produce in the following day. They proved that in equilibrium, imposing or increasing a market-based undersupply penalty rate in a period can result in a strictly larger renewable energy commitment at all prices in the associated day-ahead market, and can lead to lower equilibrium reliability in all periods with probability. Mahani et al. (2017) considered multiple energy storage nodes distributed over a power distribution network, the problem was to optimally allocate these nodes over the distribution network and to create day-ahead plans according to planned applications. Zaeim-Kohan et al. (2018) propose a multi-objective particle swarm optimization for transmission congestion management considering demand response programs (DRPs) and generation rescheduling. The objective functions included the Total operation/DR cost, the emission and the load increase of transmission lines. The proposed model was tested on two test systems (IEEE 30-bus and IEEE 118-bus test systems). Hemmati (2018) presented a unified stochastic planning on battery energy storage systems in electric power systems including wind power plants. He considered the cost of energy in the network, the investment-operational costs, and the lifetime of battery energy storage systems as objectives.

Sun et al. (2015) considered the battery-based energy storage transportation by railway transportation network. He adopted a time-space network model and integrated the hourly security-constrained unit commitment with vehicle routing problem. He used two cases to simulate the battery-based energy storage transportation. Lu and Li (2017) also considered the Energy Storage Transportation with the objective of minimizing the total system planning cost.

Barber et al. (2008) developed a Genetic Algorithm to solve the Train Timetabling Problem. The timetable for the new trains is obtained with a Genetic Algorithm (GA) that includes a guided process to build the initial population. The proposed GA is tested using real instances obtained from the Spanish Manager of Railway Infrastructure (ADIF). The results showed that GA was able to explore the search space and led to good solutions in a short time. Sun el al. (2014) proposed a multi-objective optimization model for train routing on high-speed railway network to provide a better service. Beside the average travel time of trains, the model also considers energy consumption and user satisfaction. Based on this model, an improved GA was designed to solve the train routing problem. The simulation results demonstrate that the accurate algorithm is suitable for a small- scale network, while the improved genetic algorithm based on train control (GATC) applies to a large-scale network.

The objective of this paper is to plan the transportation of battery storage system from generators or renewable energy sources to consumption nodes on large scale networks using railway system. The paper proposes a genetic algorithm model to solve the problem and be able to find:

1. The assignment of load nodes to generator nodes
2. Number of trains required
3. Number of batteries on each train
4. Best route for each train
5. Min transportation cost

3. Problem Definition

This section describes the problem and the assumptions considered in this model. For the railway network shown in Figure 1 where the nodes represent consumption/generation points and the arcs represent the rail road route from one node to another. The demand forecast of consumption nodes is known for a given time horizon. Each generator has a maximum capacity. The problem is to supply the consumption nodes with the required power. Battery Based storage system is used to store the power from the generator nodes and supply the consumption nodes. The batteries are transported using trains on the available railway system. The battery can stay idle at any point or it can be charged/discharged. The objective is to schedule the trains and determine the number of batteries needed in each train for a given planning horizon to satisfy the given demand.

The assumptions of the developed model are as follows:

1. The model plans for a given planning horizon.
2. Demand for each period within the planning horizon is known for all load nodes.

3. Max generating capacity for each generator is known.
4. Transportation time between nodes is known.
5. Charging and discharging rates are known and assumed to be constant
6. Max capacity of battery is known

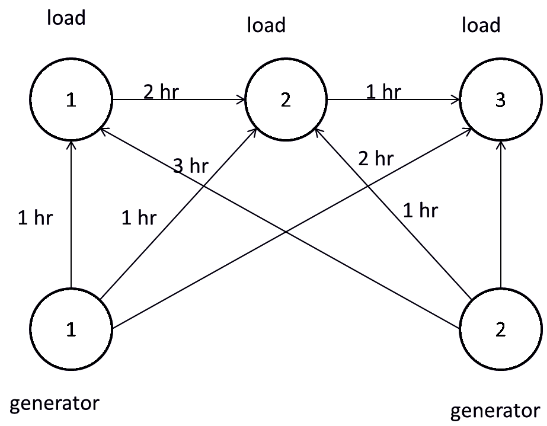

Figure 1. Railway network under consideration

To formulate the problem, the network is further divided into a time interval divisible by all the links duration. For example, the network shown in figure 1 could be divided into one hour interval, in this case, the link joining generator 2 to load node 1 is further divided into 3 one hour links with 2 auxiliary nodes added in between.

For a set of nodes I and their auxiliary Nodes I' connected by set of arcs A where $A=\{(i,j): i \text{ and } j \in I \cup I'\}$. among I there is a subset G of nodes with generators where $G \subset I$. There is N train engines available, each can pull up to N^c battery vehicles. Battery vehicles are charged at the generator nodes. Consider a planning horizon K which is a multiple of the time interval used in the auxiliary network. The problem is to supply each node by its power requirement in each time period minimizing both of the transportation cost and the number of battery vehicles required.

The following nomenclature is used in the model:

Parameters

I Set of nodes

I' Set of auxiliary nodes

G generators nodes set where $G \subset I$

N number of trains

N^c Number of battery vehicles that can be stowed by a train engine

A set of connecting arcs

K time horizon, must by a multiple of the time interval used in the auxiliary network

c_{ij} cost of transporting a battery vehicle from node i to node j.

D_{jk} demand of node *j* at time *k*.

d_1 discharge rate for a time interval when in travel

d_2 discharge rate for a time interval when idle at a node

d_3 discharge rate for a time interval when in discharging at a node or charging at a generator

Variables

x_{fijk} binary decision variable of whether vehicle *f* visits *j* just after *i* at time *k*

F number of battery vehicles required

y_{fik} binary decision variable of whether vehicle *f* is used in charging/discharging node *i* in time *k*

Q_{fk} charge of vehicle *f* at time *k*

Q_f^m max charge of vehicle *f*

Indices

i,j index of nodes from $I \cup I'$

f index of the battery

Formulation

Objective 1: Min $\sum_{i \in I \cup I'} \sum_{j \in I \cup I'} \sum_{f=1}^{F} \sum_{k=1}^{K} c_{ij} x_{fijk}$ (1)

Objective 2: Min F (2)

Subject to:

$$\sum_{i \in I \cup I'} \sum_{i \in I \cup I'} x_{fijk} = 1 \qquad \forall k \le K, f \le F \qquad (3)$$

$$\sum_{i \in I \cup I'} x_{fijk} = \sum_{i \in I \cup I'} x_{fjik+1} + x_{fjjk+1} \qquad \forall k \le K, f \le F, j \in I \cup I' \qquad (4)$$

$$\sum_{f=1}^{F} \sum_{j \in I \cup I'} Q_{fk} x_{fjk} x_{fijk} \ge D_{jk} \qquad \forall k \le K, f \le F, j \in I \cup I' \qquad (5)$$

$$Q_{fk+1} = min\,(Q_{fk} - d_1 \sum_{i \in I \cup I'} \sum_{j \in I \cup I', i \neq j} x_{fijk} - d_2 \sum_{i \in I \cup I'} x_{fiik} - d_3 \sum_{i \in \frac{I}{G}} y_{fiik} x_{fiik} + d_3 \sum_{i \in G} y_{fiik} x_{fiik}, Q_f^m) \qquad \forall k \le K, f \le F \qquad (6)$$

$$Q_{fk+1} = max(Q_{fk} - d_1 \sum_{i \in I \cup I'} \sum_{j \in I \cup I', i \neq j} x_{fijk} - d_2 \sum_{i \in I \cup I'} x_{fiik} - d_3 \sum_{i \in \frac{I}{G}} y_{fiik} x_{fiik} + d_3 \sum_{i \in G} y_{fiik} x_{fiik}, 0) \qquad \forall k \le K, f \le F \qquad (7)$$

$$\sum_{f=0}^{F} \sum_{i \in I \cup I'} \sum_{j \in I \cup I', i \neq j} x_{fjik} \le F \qquad \forall k \le K \qquad (8)$$

$$\sum_{k=0}^{L+1}\sum_{f=0}^{F}\sum_{j\in I\cup I',i\neq j} x_{fijk} \leq \sum_{k=0}^{L}\sum_{f=0}^{F}\sum_{j\in I\cup I',i\neq j} x_{fjik} + \sum_{f=0}^{F} x_{fii0} \quad \forall L<K, i\in G \tag{9}$$

$$\sum_{f=1}^{F} x_{fjik} \leq N^{c} \quad \forall k\leq K, f\leq F, i\in j\in I\cup I', j\in I\cup I' \tag{10}$$

$$\sum_{i\in I\cup I'}\sum_{j\in I\cup I'}\left(\min\left(1,\sum_{f=1}^{F} x_{fijk}\right)\right) \leq N \quad \forall k\leq K \tag{11}$$

The multi-objective model has two objectives: equation (1) minimizes the total cost of transporting the vehicles and equation (2) minimizes the number of vehicles. Equations (3) restrict the movement of a vehicle to one source/destination nodes at a given time. In equations (4), whenever a vehicle visits a node at time k, it must either stay at the same node or move to a successive node in k+1. In equations (5), the total power of all the vehicles at node j at time k is greater than the required power. In equations 6 and 7, the charge of a vehicle at time k+1 equals its charge at time k minus losses in movement, in idle, and in discharging to nodes plus charging from the generators. Equations 6 and 7 limit the max charge to the battery capacity and the minimum to be zero.

Equations (8) restrict the number of batteries to no more than F batteries. Equations (9) ensure that at any time interval, the cumulative total number of batteries coming out from the start is less than or equal to what were initially at the generator plus the number of batteries visited the generator in between. Equations (10) restrict the number of batteries used at any interval between two given nodes to be smaller than the trains' capacity. Equations (11) restrict the number of trains to be no more than the available trains at any time interval.

4. The Proposed Multi-Objective Solution Algorithm

Genetic Algorithms(GA) offer an attractive approach for effective rapid global search of large, non-linear solution spaces (Pardalos PM, Floudas CA., 2009). The trains scheduling GA model is formulated as a vehicle routing problem (VRP) in a time-space network (Yingyun Sun et al., 2015). The objective is to minimize the transportation cost and minimize the number of battery vehicles needed. The general procedure for the developed multi objective GA is shown in Figure 2. The GA starts with generating the initial population randomly as mentioned in section 4.1. Each chromosome in the initial population is evaluated by applying train assignment heuristic and using the fitness function. A new generation is formed from the elite chromosomes (best chromosomes in fitness function value), crossover children and mutated children. The same process is repeated until the stopping criteria is met which is the number of generations.

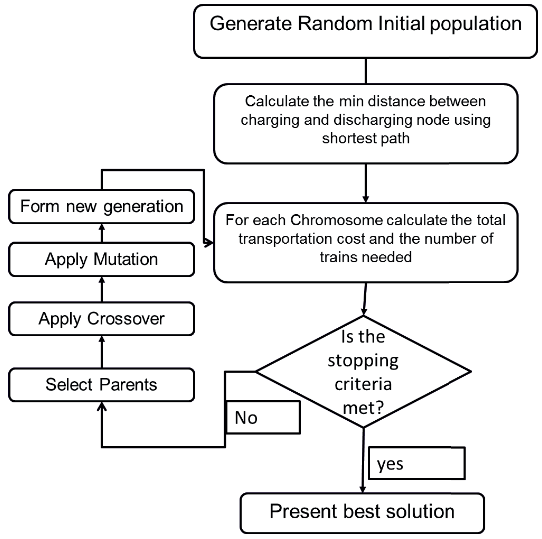

Figure 2. Flow chart of the developed model

4.1. Chromosome representation and Initial Population

The chromosome is divided into two parts as shown in figure 3. The number of genes in the first part of the Chromosome is equal to the number of trains available. Each gene represents the total power capacity of each available train (i.e., the number of batteries on this train multiplied by the battery capacity). In figure 3, the first cell means that a train with a total capacity of batteries of 200 MWh is available to use (i.e. 10 batteries each with a capacity 20 MWh). The second part of the chromosome represents the assignment of load nodes to generator nodes. The length of this part is equal to the number of load nodes that must be visited. For Each gene a random number is generated that represents the assigned generator that will supply the current load node (e.g., the fourth cell means that load node 4 will be supplied from generator node 1).

200	100	200	1	2	3	1	1

Figure 3. chromosome representation

The model allows for more than one train to be assigned to the same generator node. However, each train is allowed to visit only one generator once in the available time spam.

To evaluate the chromosomes, we propose a heuristic for train assignment to generator and load nodes (Algorithm 1). The first step in the assignment procedure is that for each generator node, a set of all nodes that are assigned to this generator is created from the chromosome. For each generator node (g) a train(N) is assigned. The train is charged at the generator node and travels to the load nodes assigned to this generator according to their order in the chromosome. If the time needed to charge the train batteries, travel to the node and discharge at that node is greater than time span allowed, then, a new train is assigned (N+1). A new train is also assigned if the remaining capacity of the batteries in the train before serving the load node is less than the demand at this load node. This train starts the journey from the generator to the rest of load nodes assigned to this generator.

When we apply the proposed algorithm on the chromosome shown in figure 4, we start by the first train and the first unassigned node. We start with train 1 which has a capacity of 200MWh (i.e., 10 batteries). The first unassigned node is node 1 which is assigned to generator 1. We then conclude that the nodes that can be possibly served by the current train are those assigned to generator 1 (i.e., nodes 1, 4 and 5). If the train has unused capacity capable of serving node one without violating the time requirement, then node one is assigned to train 1 and the next node assigned to the same generator is considered (node 4). Otherwise, the next train is considered.

In case node 1 is added, the requirement of node 4 is considered against the unused capacity in the first train along with the time requirement. If it can be feasibly served, node 4 is assigned to train 1. Otherwise, node 4 is dropped from the current possible nodes to be served by the current train and we look for the next candidate (i.e., node 5). Node 4 is then considered in train 2 and we keep iterating until all nodes are assigned to trains.

Algorithm 1: Train Assignment algorithm

1- Set g=1, N=1
2- Determine $LGset_g$ which is a set of all the load nodes(j) assigned to generator(g)
3- If $LGset_g$={ϕ} **then** go to step 6
4- Set $TLset_f$={ϕ}, $Tcap_f$=chrome(NT), $Time_{fg}$=charging time at (g)
5- For each load node(j) in $LGset_g$
    If demand of node j at time k (D_{jk})< $Tcap_N$ & $Time_{fg}$ + time from node i to j (t_{ij})+discharging time(L)<time horizon(k)
        Then $TLset_f$ ={ $TLset_f$, j}, $Time_{fg}$ = $Time_{fg}$ + time from node i to j (t_{ij})+discharging time(L)
        Otherwise N=N+1
        $TLset_f$ ={ j}, $Time_{fg}$ = charging time at (g)+time from node i to j (t_{ij})+discharging time(L)
6-If g<G **then** set g=g+1 and go to step 2 **Otherwise** go to step 7

The fitness function for the Proposed multi-objective GA model is minimizing the total transportation cost shown in Equation (12) and minimizing the number of battery vehicles needed as shown in Equation (13)

Objective 1: Min $\sum_{i \in I \cup I'} \sum_{j \in I \cup I'} \sum_{f=1}^{F} \sum_{k=1}^{K} c_{ij} x_{fijk}$ (12)

Objective 2: Min F (13)

The multi-objective GA finds the pareto front of the two objectives. This front keeps the non-dominated solutions and discards the dominated solutions. This allows the decision maker to choose the solution most suitable to the problem.

4.2. Parents Selection and Crossover

The parents are selected according to tournament selection. The Crossover used in the developed model is single point crossover. The parents are divided at the end of train capacity genes into two parts as shown in Figure 4 where the first part of the new child is taken from parent one(train capacities) and the second part from parent two (generators assignment to load nodes).

P1	**500**	**200**	**300**	**1**	**2**	**2**	**1**	**3**
P2	**400**	**300**	**100**	**4**	**3**	**3**	**1**	**2**
child	**500**	**200**	**300**	**4**	**3**	**3**	**1**	**2**

Figure 4. One-point crossover

4.3. One-Point Scramble Mutation

The mutation used in the proposed GA is one-point scramble mutation. In this mutation a binary number is generated randomly. If the selected number is equal to zero, the first part of the chromosome, which represents the trains capacity, is mutated by being completely randomly generated. On the other side, if the selected number is equal to one, the second part of the chromosome, which represents the route and the stations sequence, is mutated by randomly generating new genes for the route.

In the example shown in Figure 5, the random number is equal to one so the mutation happens to the second part of the chromosome by creating totally new genes. This method avoids being trapped in a local optimum.

Chromosome:

200	**100**	**200**	**4**	**3**	**3**	**1**	**2**

Mutated child:

200	**100**	**200**	**1**	**2**	**3**	**4**	**1**

Figure 5. One-point scramble mutation

5. Numerical Experimentation

To test the developed GA, two data set were generated 30 nodes(P30) and 90 nodes (P90). Table 1 shows the values of the two data sets parameters. The Genetic Algorithm Toolbox in Matlab 2016 is used to solve the test problems.

5.1. Results for P30 Nodes Data Set

The total number of nodes in this data set is 30 nodes, 22 of them represents the load nodes and 8 nodes represents generator nodes. The battery capacity used is 20 MWh which is equivalent to 50 feet standard rail car battery. The maximum number of batteries rail car that could be carried by a single train is 8 batteries. The time spam for the generated Schedule is 24 hours. The charging time and discharging time is 4hrs. The demand of load nodes is shown in Table 2 while the capacity of generators is shown in Table 3.

Table 1. The values of the numerical example

Parameters	P30	P90
Number of nodes (*I*)	30	90
Generators nodes (*G*)	6	40
Load Nodes (*L*)	24	50

Max Number of trains (N)	30	40
Number of battery vehicles (N^c)	8	8
Max Charge of Battery	20 MWh	50 MWh
Time horizon (K)	24 hr	24 hr
Charging and Discharging	4 hr	4 hr
Genetic Parameters	Value	Value
Population size	400	400
Generations	3000	3000
Crossover rate	0.7	0.7

Table 2: The Demand At Load Nodes

Node	Demand	Node	Demand
1	11	**12**	9
2	14	**13**	3
3	7	**14**	9
4	3	**15**	2
5	12	**16**	17
6	10	**17**	8
7	5	**18**	10
8	11	**19**	3
9	6	**20**	10
10	8	**21**	4
11	3	**22**	10

Table 3: Generator Nodes Capacity

Node	Capacity
1	80
2	55
3	50
4	80
5	80
6	50
7	80
8	55

To evaluate the effectiveness of the developed genetic algorithm the model is used for a single objective which is the transportation cost. Figure 5 shows that the model converges with the increase in generation number. To illustrate the multi-objective results, figure 6 shows the pareto front for the two objectives: the transportation cost and the number of battery vehicles. Figure 7 shows that the results of the model are consistent when tested on different runs.

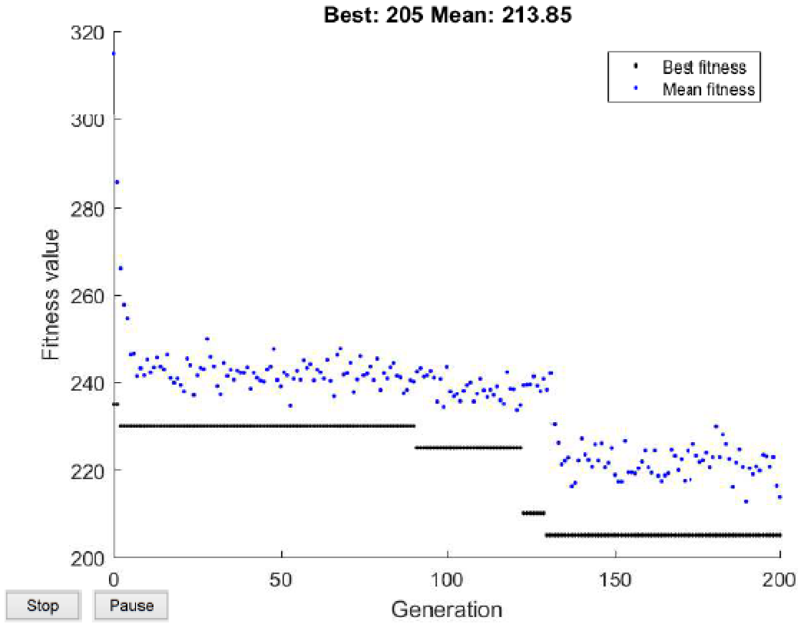

Figure 7. The best and the mean fitness value (transportation cost) plotted against generations for 30 node data set

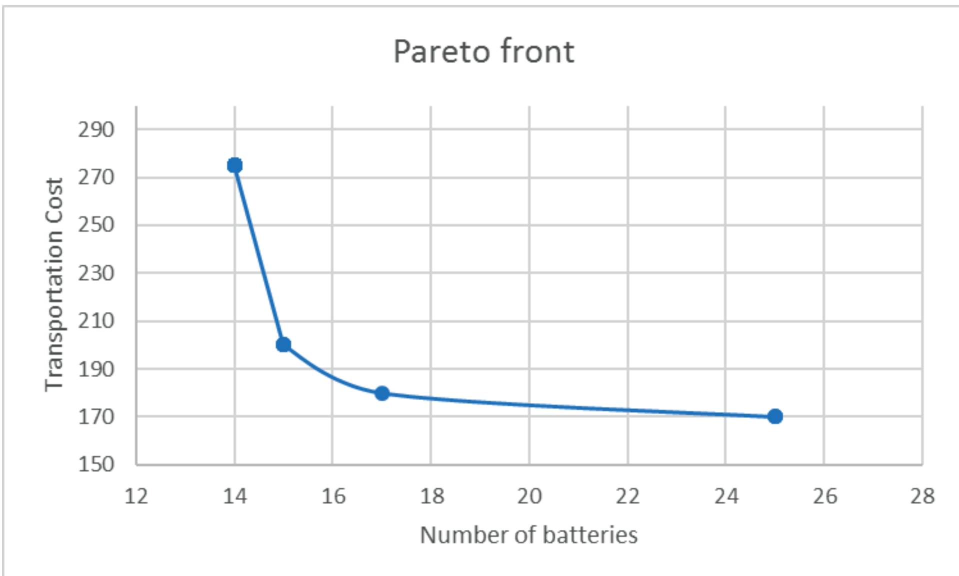

Figure 8. The pareto front for the P30 data set

To illustrate the output of the train assignment heuristic, tables 4-7 are used. Table 4 shows the results of the first part of the chromosome of one of the points on the Pareto front. More specifically, it shows the capacity of the batteries installed on the available trains. Table 5 shows the assignment of the load nodes to the generators for the same point on the Pareto front. Table 6 shows the route of each train from the generator to the load nodes and the actual number of trains needed to satisfy the demand. Table 7 shows the charging and discharging schedule for train 1.

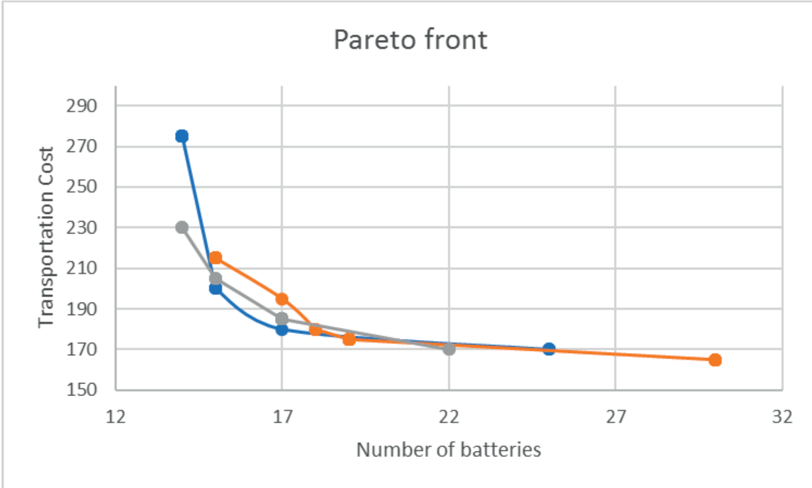

Figure 9. The Pareto Front for Three Runs of The P30 Data Set

Table 4. Solution of One Point On The Pareto Front With Minimum Transportation Cost

Capacity of the trains	20	40	60	20	40	40	40	40	60	100

Table 5. Generator Load Assignment

Load node	1	2	3	4	5	6	7	8	9	10	11
Generator	25	26	23	26	30	25	23	30	28	29	24
Load node	12	13	14	15	16	17	18	19	20	21	22
Generator	26	30	29	26	28	23	25	28	26	29	24

Table 6: Generator Load Train Assignment

Generator	Train assignment	Train Route		
23	1	3	7	17
24	2	11	22	
25	3	1	6	18
26	4	2	4	
26	5	12	15	20
28	6	9	16	19
29	7	10	14	21
30	8	5	8	13

Table 7: Charging and Discharging Schedule

Time span	0-4	4-5	5-9	9-12	12-16	16-20	20-24
Battery location	23	23-3	3	3-7	7	7-17	17
status	charging	transportation	discharging	transportation	discharging	transportation	discharging

5.2. Results for P90 data set

The number of nodes in this data set is 90 and the number of available generators is 40. The battery capacity is 50 MWh and the maximum number of batteries rail cars that could be carried by a single train is 8 batteries. The time spam for the generated Schedule is 24 hours. The charging time and discharging time is 4hrs. The Demand at load nodes is given in Table 7 while the capacities of the generators are given in Table 8. The pareto front for the P90 is shown in Figure 8. The number of points in this set is greater than the P30 as solution space is much bigger.

Table 8: The Demand at Load Nodes

node	Demand	node	demand	node	demand	node	demand	node	demand
1	55	**11**	96	**21**	19	**31**	37	**41**	17
2	22	**12**	27	**22**	26	**32**	37	**42**	18
3	42	**13**	12	**23**	46	**33**	18	**43**	23
4	32	**14**	64	**24**	63	**34**	16	**44**	113
5	56	**15**	48	**25**	25	**35**	53	**45**	63
6	21	**16**	20	**26**	63	**36**	28	**46**	84
7	75	**17**	15	**27**	36	**37**	34	**47**	12
8	50	**18**	11	**28**	33	**38**	20	**48**	12
9	37	**19**	8	**29**	27	**39**	87	**49**	277
10	15	**20**	66	**30**	20	**40**	17	**50**	78

Table 9: Generator Nodes Capacity

Node	capacity	Node	capacity	node	capacity	node	capacity
51	50	**61**	50	**71**	350	**81**	500
52	50	**62**	300	**72**	50	**82**	550
53	300	**63**	350	**73**	50	**83**	50
54	350	**64**	300	**74**	100	**84**	50
55	50	**65**	50	**75**	50	**85**	100
56	50	**66**	100	**76**	100	**86**	300
57	100	**67**	50	**77**	50	**87**	100
58	50	**68**	50	**78**	50	**88**	50
59	100	**69**	50	**79**	50	**89**	50
60	350	**70**	300	**80**	50	**90**	100

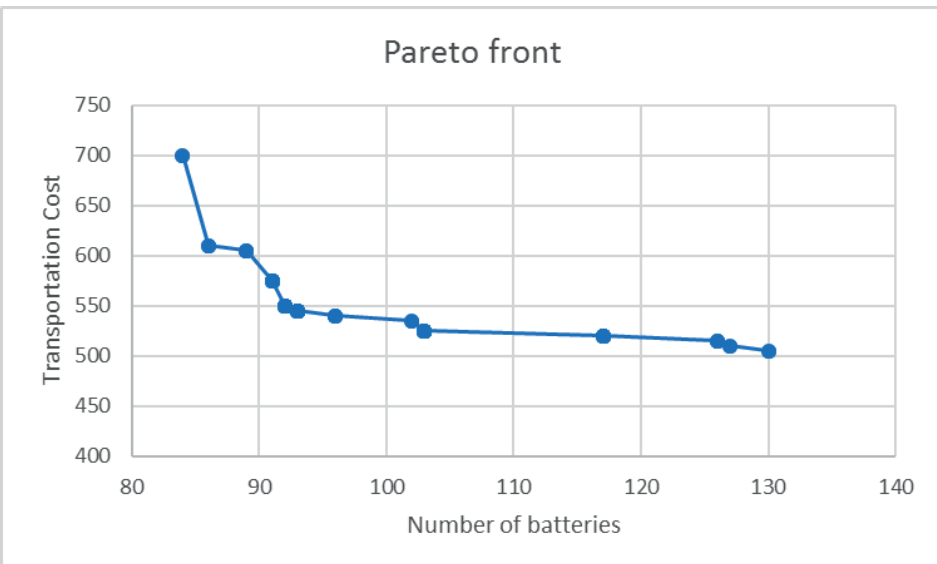

Figure 10: The Pareto Front for the 90-Node Data Set

6. Conclusion

This paper considers the use of railway network to transport the Battery Energy storage system from the generators to areas with high demand or areas that are not linked with transmission lines. The objective is to minimize the total transportation cost and the number of battery vehicle required. After defining the problem as a constrained multi-objective optimization problem, multi-objective genetic algorithm was used to solve it. Two data sets were generated to test the developed GA (P30 and P90 data set). The results show the effectiveness of the proposed algorithm and its ability to converge and to provide good solutions for the problem for small and large instances. The Battery Energy storage system provides a good solution to transport the energy from renewable energy sources to areas with high demand. Future work can include extending this model by including passengers train schedules. With recent environmentally friendly and renewable power generation projects in Egypt, real application of the model on the Egyptian power distribution system can be considered.

7. References

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