

Article

Optimal Energy Management of Railroad Electrical Systems with Renewable Energy and Energy Storage Systems

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Abstract: The proposed optimal energy management system balances the energy flows among the energy consumption by accelerating trains, energy production from decelerating trains, energy from wind and solar photovoltaic (PV) energy systems, energy storage systems, and the energy exchange with a traditional electrical grid. In this paper, an AC optimal power flow (AC-OPF) problem is formulated by optimizing the total cost of operation of a railroad electrical system. The railroad system considered in this paper is composed of renewable energy resources such as wind and solar PV systems, regenerative braking capabilities, and hybrid energy storage systems. The hybrid energy storage systems include storage batteries and supercapacitors. The uncertainties associated with wind and solar PV powers are handled using probability distribution functions. The proposed optimization problem is solved using the differential evolution algorithm (DEA). The simulation results show the suitability and effectiveness of proposed approach.

Keywords: electric railroad systems; energy storage; renewable energy; optimal power flow; probability distribution; regenerative braking

1. Introduction

Nowadays, electrical systems are facing several new challenges to deal with the integration of intermittent renewable-based energy sources. These renewable energy resources (RERs) are characterized by volatile, partially unpredictable, and mostly non-dispatchable generation. However, the increasing concerns over greenhouse gas emissions and energy prices are forcing us to move toward finding new energy alternatives. In recent years, to meet the increasing electrical demand for electrical traction and with the introduction of the deregulation market, there is a need for handling this situation with the help of integrated technology. During the last decade, there has been a tremendous interest in the world to develop high-speed railroad systems and enable their efficient operation. The railroad power networks consist of territorially dispersed substations that have electrical traction capability for passenger traffic. If the distance between these substations is long, then these are more suitable for the integration of RERs and storage systems. Integrating RERs and storage systems into the railroad network has reduced the dependence on the primary electrical grid [1].

Electric trains can generate electrical energy while braking using the regenerative brakes, and the energy storage systems can facilitate harvesting the generated energy. Regenerative braking plays a vital role for improving the energy efficiency of railroad systems. The energy obtained in regenerative braking is fed back to the utility grid or stored in the energy storage systems. To optimize the energy obtained from the regenerative braking, the energy storage systems are used in the system. The energy storage systems can be on-board or wayside storages. In on-board energy storage systems,

the energy is stored during the regenerative braking process, and it is used to the same train during the next acceleration process. In contrast, the wayside energy storage systems are installed in a substation or near a substation, and they absorb the regenerative braking energy that cannot be used in the system instantaneously and deliver this energy to accelerate another train in the same electric section [2]. The electrical supply of the railroad system is very convenient/favorable for installing the RERs and storage systems along with regenerative braking capabilities.

A comprehensive set of steady-state approaches to be included in the power flow simulation studies of direct current (DC) railway systems is proposed in [3]. An approach for the optimal operation of railroad electrical systems considering RERs, regenerative braking, and hybrid energy storage systems is proposed in [4]. An overview of energy storage, which plays a crucial role in maintaining a reliable and robust modern electric system in RERs, is presented in [5]. A mathematical approach for implementing multi-rate analysis in railroad traction systems by means of heterogeneous multi-scale approaches is presented in [6]. Arbolea et al. [7] suggests that on-board accumulation is the best option for energy recovery in a safe way in light railroad systems from the point of view of investment cost and flexibility. An approach based on a backward/forward sweep technique for solving power flows in weakly meshed DC traction systems is presented in [8]. A new coupled modeling method for the analysis of the energetic optimization of railways and based on the use of object-oriented language (MATLAB-SimscapeTM) is proposed in [9].

Ghaviha et al. [10] presents the application of energy storage devices used in railway systems for increasing the effectiveness of regenerative brakes. A comparative study of two hybrid energy storage systems of a two-front wheel-driven electric vehicle is presented in [11]. Two simulation approaches—to reproduce the behavior of high-speed trains when entering in a railway node, and to analyze the impact of regenerative braking in DC railways, including the usage of storage systems—have been developed in [12]. The problem of optimally sizing the hybrid storage systems installed in railway systems, considering the effect of regenerative braking, is proposed in [13]. The recent application of energy storage devices in electrified railways, especially flywheels, batteries, electric double-layer capacitors, and hybrid energy storage devices is presented in [14]. Lithium-ion and lead-acid type batteries are used in electrified railways in Japan, and flywheels are used for energy saving in light railroad vehicles. The feasibility of implementing Smart Grid (SG) technologies at the railway network scale and providing the energy management of hybrid railway power substations is analyzed in [15]. An optimization model for railroad transportation systems with the integrated SG is proposed in [16]. A green solution to recover trains' braking energy by integrating the smart DC microgrid concept in railroad systems is proposed in [17]. The proposed green solution is based on storing excess braking energy and using it in auxiliary loads in a station or in proximity. A dual-objective optimization problem for the simultaneous optimization of substation energy consumption and the total cost of an energy storage system is proposed in [18]. The practical energy-saving operation approach obtained through the study of energy-saving operation and its practical use in commercial operation is described in [19].

In recent years, there has been a pressing need for improving the energy efficiency operation of railways. According to the above literature review, it can be observed that the usual energy analysis approach of trains considers a static analysis based on the power flow formulations. However, in the presence of RERs, i.e., wind and solar photovoltaic (PV) powers, the static analysis is not sufficient, as wind speed and solar irradiance are intermittent in nature. In the same context, in the presence of energy storage systems, the charging and discharging modes cannot be handled using the static tools. Therefore, this paper proposes an optimization approach that can handle these difficulties. The main contributions of this paper are as follows:

- Proposes an optimal operation of a railroad electrical system including renewable energy resources (RERs), a hybrid energy storage system (battery storage and supercapacitors), and the regenerative braking capabilities of trains.

- Formulates an AC optimal power flow (AC-OPF) problem by considering the total operating cost minimization objective of a railroad electrical system subjected to various equality and inequality constraints.
- Handles the uncertainties associated with wind and solar PV powers by using probability distribution functions.
- Solves the proposed optimization problem by using the differential evolution algorithm (DEA).
- Simulates four different case studies by considering the RERs and hybrid energy storage systems.

The rest of this paper is organized as follows: Section 2 presents the modeling and uncertainty handling of renewable energy resources and energy storage systems. Then, the proposed problem formulation is described in Section 3. Then the description of differential evolution algorithm is presented in Section 4. Then, the simulation results and discussions are presented in Section 5. Finally, the contributions of the paper along with concluding remarks are presented in Section 6.

2. Modeling of Renewable Energy Resources and Energy Storage Systems

As mentioned before, in this paper, wind and solar PV energy systems are considered as RERs, and they are modeled as follows.

2.1. Modeling and Uncertainty Handling of Wind Energy System

The wind energy generator (WEG) converts the kinetic energy of wind into electrical energy. The output power of WEG at a specific location depends on the wind speed at hub height and speed characteristics of the turbine. The power output of WEGs varies accordingly to the wind speed, and it closely follows the Weibull probability distribution function. The power output of WEG (P_W) (i.e., wind speed to wind power conversion function) is expressed by using Equation (1) [20]:

$$P_W = \begin{cases} 0 & \text{if } v < v_{ci} \text{ or } v \geq v_{co} \\ P_r \left(\frac{v^3 - v_{ci}^3}{v_r^3 - v_{ci}^3} \right) & \text{if } v_{ci} \leq v \leq v_r \\ P_r & \text{if } v_r \leq v \leq v_{co} \end{cases} \quad (1)$$

where v is wind speed in m/s; v_r , and v_{ci} and v_{co} are the rated, cut-in and cut-out wind speeds in m/s. P_r is the rated wind power output. The power output from WEG (P_W) is limited by the upper/maximum power limit (P_W^{max}) and it is expressed as:

$$P_W \leq P_W^{max} \quad (2)$$

As mentioned before, in this work, the Weibull probability density function (PDF) of wind speed is used, and it is expressed as:

$$f_v = \left(\frac{k}{c} \right) \left(\frac{v}{c} \right)^{k-1} e^{-\left(\frac{v}{c} \right)^k} \quad 0 < v < \infty \quad (3)$$

where c and k are the scale and shape factors, respectively. The value of c ranges from 10 to 20 m per hour, and k ranges from 1.5 to 2.5. Here, random variable transformation is used to accomplish the wind speed random variable (i.e., v) to wind power random variable (i.e., P_W). By using linear variable transformation, the probability distribution function is in a continuous range (i.e., $v_{ci} \leq v \leq v_r$), and it can be expressed as [20]:

$$f_{P_W} = \frac{k(v_r - v_{ci})}{C^k P_r} \left[v_{ci} + \frac{P_W}{P_r} (v_r - v_{ci}) \right] e^{-\left[v_{ci} + \frac{P_W(v_r - v_{ci})}{P_r} \right]^k} \quad (4)$$

2.2. Modeling and Uncertainty Handling of Solar Energy System

The solar energy system directly converts sun energy into electricity. The solar PV power output depends on natural conditions such as solar irradiation and temperature, and it is expressed as (Reference [21]):

$$P_S = f(G, T) \quad (5)$$

However, for the sake of simplicity, the effect of temperature is not considered in this paper. Therefore, the obtained power output from the solar PV unit depends only on solar irradiance, and it can be expressed as [22]:

$$P_S = \begin{cases} P_r^S \left(\frac{G^2}{G_{std} R_c} \right) & \text{if } 0 < G < R_c \\ P_r^S \left(\frac{G}{G_{std}} \right) & \text{if } G > R_c \end{cases} \quad (6)$$

where G is the forecasted solar irradiation, G_{std} is the standard solar irradiation 1000 W/m^2 , P_r^S is the rated power generation from solar PV unit, and R_c is a certain solar irradiation set at 150 W/m^2 . The power output from solar PV generator (P_S) is limited by the maximum/upper limit (P_S^{max}), and it is expressed as [22]:

$$P_S \leq P_S^{max} \quad (7)$$

Generally, the hourly solar irradiation is modeled by a probabilistic distribution, because the historical solar irradiation data is often accessible and sufficient to justify such representation. The collected historical data over long periods of time can be used to characterize the probabilistic behavior of irradiance. This hourly solar irradiation typically follows a bimodal distribution, due to the presence of cloudy periods. The bimodal distribution can be considered as a linear combination of two unimodal distributions. These unimodal functions can be modeled by using Log-normal, Weibull, and Beta PDFs. In this work, Weibull PDF is used, and it can be expressed as [21]:

$$f_G = W \left(\frac{k_1}{c_1} \right) \left(\frac{G}{c_1} \right)^{k_1-1} e^{-\left(\frac{G}{c_1}\right)^{k_1}} + (1-W) \left(\frac{k_2}{c_2} \right) \left(\frac{G}{c_2} \right)^{k_2-1} e^{-\left(\frac{G}{c_2}\right)^{k_2}} \quad 0 < G < \infty \quad (8)$$

where W is the weight parameter, and it is in the range of ($0 < W < 1$); and c_1 , c_2 , k_1 and k_2 are the scale and shape factors, respectively.

2.3. Modeling of Hybrid Energy Storage System

As explained before, in this paper, the storage batteries and supercapacitors are considered as hybrid energy storage systems, and they ensure the storage flexibility. Different energy storage systems need to be integrated to adapt the changes required to integrate RERs and handle the problem of fluctuation of RERs. Batteries have high energy density, but have relatively low power density, a small number of charging/discharging cycles, and their characteristics will degrade quickly over time. Therefore, batteries cannot be used in isolation to store the regenerative braking energy. Supercapacitors store the energy electrostatically, which gives high power density, and last for millions of charge/discharge cycles without losing energy storage capacity. However, the supercapacitors are extremely expensive. Therefore, a hybrid energy storage system is used in this work consisting of batteries and supercapacitors. The hybrid storage system combines the advantages of both the storages by improving the voltage regulation and reducing the power losses [23].

2.3.1. Modeling of Battery Storage

The charge/discharge equation of battery storage is expressed as [13]:

$$C_B^{t+1} = C_B^t - \frac{\Delta t}{C_B^m} \left(\frac{P_{B,t}^{disch}}{\eta_B^{disch}} + \eta_B^{ch} P_{B,t}^{ch} \right) \quad (9)$$

where C_B^t and C_B^{t+1} are the normalized state-of-charge (SOC) of battery storage at t and $t + 1$ time instants. Δt is the time interval studied. C_B^m is the maximum/rated capacity of battery storage. η_B^{ch} and η_B^{disch} are the charging and discharging efficiencies of storage batteries. $P_{B,t}^{ch}$ and $P_{B,t}^{disch}$ are the charging and discharging powers of a battery storage system [13].

2.3.2. Modeling of Supercapacitors

The charge/discharge equation of supercapacitors is expressed as [13]:

$$C_{SC}^{t+1} = C_{SC}^t - \frac{\Delta t}{C_{SC}^m} \left(\frac{P_{SC,t}^{disch}}{\eta_{SC}^{disch}} + \eta_{SC}^{ch} P_{SC,t}^{ch} \right) \quad (10)$$

where C_{SC}^t and C_{SC}^{t+1} are the normalized SOC of supercapacitors at t , $t+1$ time instants. C_{SC}^m is the maximum/rated capacity of supercapacitors. η_{SC}^{ch} and η_{SC}^{disch} are the charging and discharging efficiencies of supercapacitors. $P_{SC,t}^{ch}$ and $P_{SC,t}^{disch}$ are the charging and discharging powers of supercapacitors.

Probability analysis is used to handle the uncertainties related to train demands, wind, and solar PV powers. In this work, the stochastic optimization approach presented in reference [22] is used to solve the proposed optimal scheduling problem of a railroad electrical system. The other robust and stochastic optimization approaches that are presented in the literature include references [24,25], and they are used to mitigate the impacts caused by uncertainties in the energy scheduling.

3. Proposed Problem Formulation

The railroad system considered in this work is composed of RERs (i.e., wind and solar PV energy systems) and regenerative braking capabilities, along with energy storage systems. The energy storage system consists of storage batteries and supercapacitors. These hybrid energy storage systems provide storage flexibility in the system. The supercapacitor technology is based on electrochemical double-layer capacitors. The advantages of supercapacitors compared to storage batteries include a higher cycle life and capacity to capture energy peaks, due to their fast response. Therefore, the supercapacitors capture high frequency and the high power density operation of regenerative braking. In contrast, storage batteries are suitable for low frequency, high energy density periods of operation, and they absorb short peaks of energy. If only batteries are used, then their lifetime would be very limited, while when only supercapacitors are used, then their high price leads to them being extremely expensive. Therefore, in this paper, a hybrid storage system with batteries and supercapacitors is considered. Figure 1 depicts the railroad electrical power system with RERs and storage systems. In this work, the train loads are considered as non-controllable loads [26]. As mentioned before, the uncertainties in wind and solar PV powers as well as train loads are modeled using the probability distribution functions. For the sake of simplicity, the investment cost of the railroad system has not been considered in this paper.

Here, an AC-OPF problem is formulated with the objective of minimizing the total operating cost (TOC) of a railroad electrical system subjected to various equality and inequality constraints, and it can be formulated as shown below (reference [4,27]).

$$\text{Minimize} \quad \sum_{i=1}^N C_G(P_{Gi}) + \sum_{j=1}^{N_W} C_W(P_{Wj}) + \sum_{k=1}^{N_S} C_S(P_{Sk}) + \sum_{b=1}^{N_B} C_B^b + \sum_{u=1}^{N_U} C_U^u - \sum_{l=1}^{N_{sp}} C_{sp}(P_{ex,l}) \quad (11)$$

The first term in Equation (11) represents the cost of power generation from the external power system (i.e., power bought from the electric network) [4], and it is calculated by using:

$$C_G(P_{Gi}) = C_G \cdot P_{Gi} \quad (12)$$

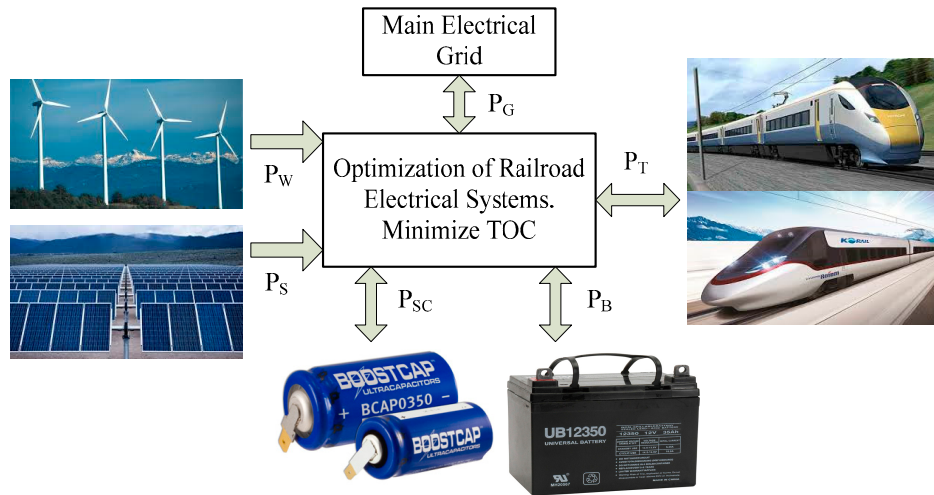


Figure 1. Railroad electrical power system with renewable energy resources (RERs) and storage systems.

The second term in Equation (11) is the cost associated with WEGs, and it is represented by [22]:

$$C_W(P_{Wj}) = a_j + C_W \cdot P_{Wj} \quad (13)$$

The third term in Equation (11) is the cost associated with solar PV units, and it is represented by [22]:

$$C_S(P_{Sk}) = b_k + C_S \cdot P_{Sk} \quad (14)$$

The fourth term in Equation (11) is the daily minimum battery storage unit cost (C_B^b in \$), which is calculated based on the condition that the battery may reach the end of its useful life in two different ways, i.e., the maximum number of years that the storage batteries can function (T_B) or the maximum number of cycles (T_{NC}), before reaching T_B . This cost is expressed as [13]:

$$C_B^b = \max \left[\frac{C_B^m}{365 \cdot T_B}, \frac{C_B^m}{\left(\frac{T_{NC}}{\delta^b} \right)} \right] \quad (15)$$

where C_B^m is the minimum storage battery cost (in \$), and δ^b is the maximum daily number of cycles per battery. The fifth term in Equation (11) represents the daily minimum cost of supercapacitors (C_U^u in \$), and this cost depends on the maximum number of years that the supercapacitors can function (T_U). This cost is expressed as [13]:

$$C_U^u = \frac{C_U^m}{365 \cdot T_U} \quad (16)$$

where C_U^m is the minimum supercapacitor unit cost (in \$). Finally, the last term in Equation (11) depicts the income obtained by selling the excess power back to the power network, and it can be expressed as [14]:

$$C_{sp}(P_{ex,l}) = C_{sp} \cdot P_{ex,l} \quad (17)$$

The above problem is solved subjected to the following equality and inequality constraints.

3.1. Equality Constraints

Equality constraints represent the nodal power balance constraints. These include the active and reactive power balance equations. The active power balance equation at a node is expressed as [4]:

$$\begin{aligned} & (P_{Gi} + P_{Wj} + P_{Sk} + P_B^{disch} + P_{SC}^{disch}) - (P_T + P_{Di} + P_{ex,l}) \\ & = V_i \sum_{j=1}^n V_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \end{aligned} \quad (18)$$

The reactive power balance equation at a node is expressed as [4]:

$$(Q_{Gi} + Q_{Wj} + Q_{Sk}) - (Q_T + Q_{Di}) = V_i \sum_{j=1}^n V_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \quad (19)$$

3.2. Inequality Constraint

The active and reactive power outputs from the network are restricted by their minimum and maximum limits, and they are expressed as [4]:

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \quad (20)$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \quad (21)$$

The voltages at each node are restricted by their minimum and maximum limits, and they are expressed as:

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max} \quad (22)$$

The line flow/power flow of a line is limited by [4]:

$$S_{Li} \leq S_{Li}^{max} \quad (23)$$

The other inequality constraints include Equations (2) and (7).

From the above objective function and constraints, it is clear that this optimization problem is a non-linear programming problem, and it is solved using the differential evolution algorithm (DEA). The description of DEA is presented in the next section.

4. Differential Evolution Algorithm (DEA)

DEA is a stochastic, population-based evolutionary optimization technique that was introduced by Storn and Price in 1995. DEA is developed to optimize the real parameter and real valued functions. It can be used for solving various practical problems considering the non-linear, non-continuous, non-differential, and multi-dimensional features. The probabilistic distribution for the generation of offspring is not required for the DEA. This leads to less computational burden and less mathematical operations. An overview of DEA is depicted in Figure 2 [28].

As mentioned earlier, DEA is a population-based optimization technique that consists of initialization, mutation, crossover, and selection operators. A brief description of these operators is presented as follows.

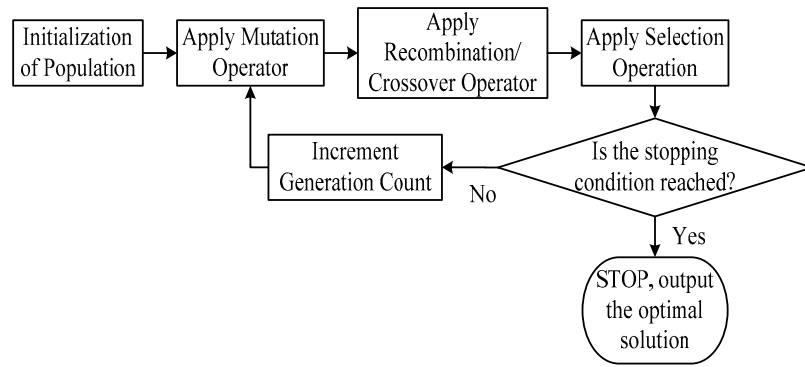


Figure 2. Overview of differential evolution algorithm (DEA).

4.1. Initialization

Define each chromosome/variable of population for a given problem between their lower (x_j^L) and upper (x_j^U) bounds, i.e.:

$$x_j^L \leq x_{j,i} \leq x_j^U \quad (24)$$

Randomly initialize a population of chromosomes of size N. Initialize the population members by using [29]:

$$x_{j,i}(0) = x_j^L + \text{rand}(x_j^U - x_j^L) \quad (25)$$

where *rand* is a random number between 0 and 1.

4.2. Mutation Operation

The main aim of the mutation operator is to expand the search space. For a given chromosome ($x_{j,i}$), randomly select three vectors $x_{r1,i}$, $x_{r2,i}$, and $x_{r3,i}$; in such a way that i , $r1$, $r2$, and $r3$ are distinct. Then, add the weighted difference of two vectors to the third one using [29]:

$$v_i^{j+1} = x_{r1,j} + k(x_{r2,j} - x_{r3,j}) \quad (26)$$

where k is a mutation factor between 0 and 2, and v_i^{j+1} is a donor vector.

4.3. Crossover Operation

There are two variants of crossover operators that are available in the literature, i.e., binomial crossover and exponential crossover. In this paper, binominal crossover is used. By using this crossover operator, the generated child $U_{i,i}(t)$ is expressed as [29]:

$$U_{i,i}(t) = \begin{cases} v_{i,j}(t) & \text{if } \text{rand}_{j,i} \leq CR \\ x_{i,j}(t) & \text{if } \text{rand}_{j,i} > CR \end{cases} \quad (27)$$

where CR is the crossover rate, and $U_{i,i}(t)$ is the child that will compete with the parent $x_{i,j}(t)$.

4.4. Selection Operation

In the selection process, DEA uses the principle of survival of the fittest. This process is carried out to keep the population size constant and to find the child and parent chromosomes that will be selected for the next generation [30]:

$$x_i^{t+1} = \begin{cases} U_i(t) & \text{if } f(U_i(t)) \leq f(x_i(t)) \\ x_i(t) & \text{otherwise} \end{cases} \quad (28)$$

where $f(\cdot)$ is the objective function to be optimized. The crossover, mutation, and selection operators will continue until the stopping criterion is reached.

5. Results and Discussion

The effectiveness and suitability of the proposed model is examined on a sampled test system presented in [31,32]. In this paper, it is assumed that P_{Gi}^{min} is -6 MW, which means that 6 MW of regenerative power can be fed back to the power grid, and the power consumed from the utility/power grid (P_{Gi}^{max}) is 12 MW. It is assumed that trains are running in both directions. The optimization problem formulated in Equation (11) is solved using the DEA and implemented using MATLAB software. The parameters of DEA play a vital role in achieving the results of the proposed optimal scheduling approach [33]. Initially, several runs are performed with different values of parameters such as the mutation rate, crossover rate, population size, and maximum number of generations. The parameters considered in this work are: population size, 30; crossover rate, 0.9; mutation factor, 0.7; and the maximum number of generations, 200. All these parameters are selected after several trial runs. In this work, two trains are considered, and the demand/generating power data of trains 1 and 2 used in the simulations is presented in Figure 3.

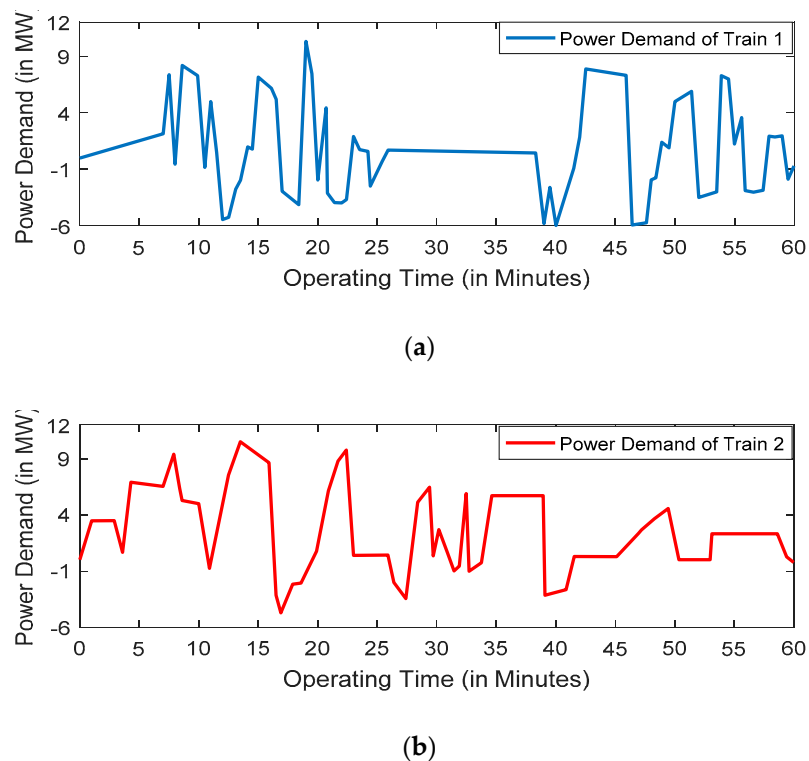


Figure 3. Power demands data used in simulation studies: (a) power demand of train 1; (b) power demand of train 2.

Here, the simulations are performed by considering the time period of 1 h (time period of (17:00–18:00) with a time step (i.e., Δt) of 30 s, which yields 120 30-s periods. When that has been done, the computational burden can be reduced significantly. The electricity/energy prices are generally available on an hourly basis; however, for the sake of simulation, in this paper, it is assumed that the energy price data is available for every 5 min for the operating period of 1 h, and it is presented in Table 1 [27].

Table 1. Energy price data for the operating period (1 h).

Time (Min.)	Energy Price (\$/MWh)	Time (Min.)	Energy Price (\$/MWh)
(0–5)	75	(30–35)	80
(5–10)	80	(35–40)	88
(10–15)	85	(40–45)	75
(15–20)	70	(45–50)	78
(20–25)	76	(50–55)	70
(25–30)	82	(55–60)	85

In this paper, four different case studies are performed to validate the performance of the proposed approach by comparing the impact of RERs and hybrid energy storage, and they are:

- Case Study 1: Railroad operation without considering RERs and energy storage systems (base case).
- Case Study 2: Railroad operation considering RERs.
- Case Study 3: Railroad operation considering hybrid energy storage systems.
- Case Study 4: Railroad operation considering RERs and hybrid energy storage systems.

The simulation results for the above four case studies are presented in the following sections.

5.1. Case Study 1

In this case, the railroad systems operation is performed without considering the RERs or energy storage systems, and the excess power does not feed back to the grid (this case is termed as the base case). However, the regenerative braking has been considered in this case. In this case, the objective function (i.e., Equation (11)) consists only of the first and last terms, as this case doesn't consist of RERs and energy storage systems. As mentioned before, in this paper, DEA is used to solve the proposed optimization problem. The amount of power delivered or absorbed by the power grid is depicted in Figure 4. Table 2 presents the optimum objective function values for the case studies 1, 2, 3, and 4. Here, the obtained total generation is 4.748 MWh, the excess energy is 1.142 MWh, and the corresponding total cost of operation is \$325.94 per hour. The computational time required for this case is 18.26 s.

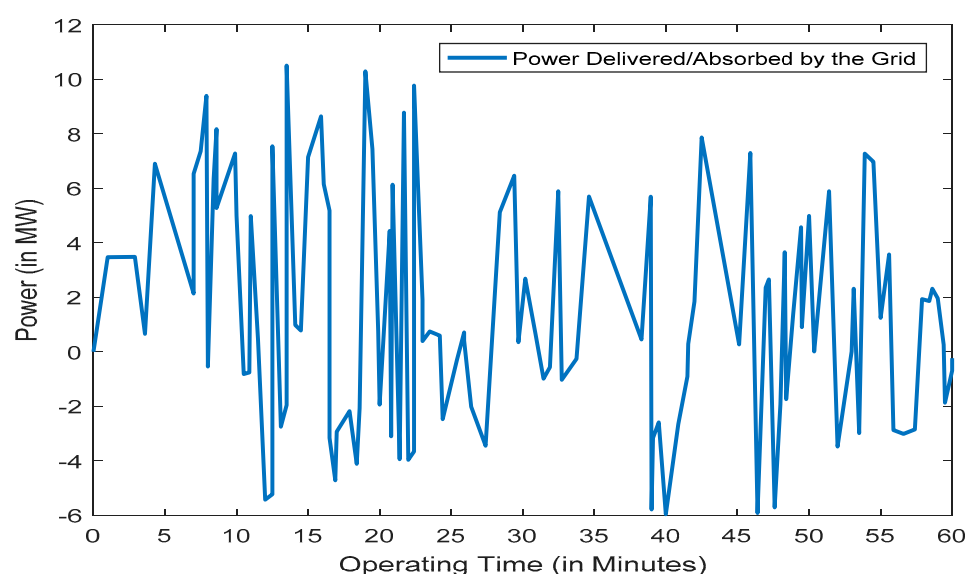
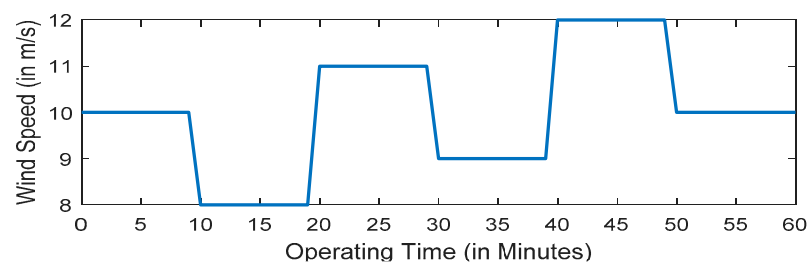
**Figure 4.** Power delivered/absorbed by the grid.

Table 2. Optimum objective function values for the case studies.

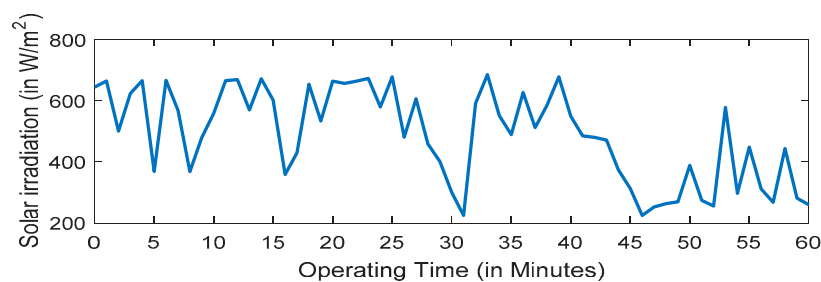
	Case Study 1	Case Study 2	Case Study 3	Case Study 4
Total Generation (MWh)	4.748	4.051	4.247	3.862
Wind Power Generation (MWh)	-	1.230	-	1.160
Solar PV Power Generation (MWh)	-	0.832	-	0.816
Battery Energy Storage (MWh)	-	-	0.421	0.382
Supercapacitor Energy Storage (MWh)	-	-	0.293	0.241
Excess Energy (MWh)	1.142	1.496	1.237	1.318
Total Cost (\$/h)	325.94	306.82	290.22	283.40
Cost Saving (%)	-	5.87	10.96	13.05
Computational Time (s)	18.26	18.90	19.05	19.22

5.2. Case Study 2

In this case, the railroad system operation is performed by considering the RERs, i.e., wind and solar PV energy systems (i.e., base case operation by including the RERs). In this work, the maximum capacity of wind power generating system (P_r) is considered to be 3 MW, v_{ci} is 3 m/s, v_r is 12 m/s, and v_{co} is 20 m/s. It is assumed that during the operating period (17:00–18:00), the forecasted wind speed is depicted in Figure 5a, and the available wind power output is calculated by using Equation (1).



(a)



(b)

Figure 5. Data of RERs in the operating period: (a) wind speed data; (b) solar irradiation data.

However, this power depends on the wind power uncertainty. Here, the Weibull probability distribution function is used to handle the wind power uncertainty. In this case, the maximum capacity of the solar PV power generating system (P_r^S) is considered to be 2 MW. The forecasted solar irradiation during the operating period is depicted in Figure 5b. For this irradiation, the obtained solar PV power output is calculated by using Equation (6). Here, the bi-modal distribution function based on the Weibull PDF is used to handle the solar PV power uncertainty.

In this case, the objective function (i.e., Equation (11)) consists of all the terms except for the fourth and fifth terms, as this case doesn't consist of the energy storage systems. The total power absorbed from the grid, wind, and solar PV power generations obtained in this case are 4.051 MWh, 1.230 MWh, and 0.832 MWh, respectively. The optimum operating cost obtained in this case is \$306.82 per hour, which is 5.87% less than the cost obtained from base case (i.e., case study 1). The computational time required for this case is 18.90 s.

5.3. Case Study 3

In this case, a hybrid energy storage system considering storage batteries and supercapacitors is utilized for the simulation (i.e., base case operation including the energy storage systems). Generally, supercapacitors are used to store the regenerative braking energy, and the storage batteries are used to compensate for the difference in electricity prices throughout the day. The operating costs of trains can be reduced by increasing the storage capacity of batteries (C_B^m) and supercapacitors (C_{SC}^m). However, it leads to an increase in the investment cost of the storage system. Therefore, a cost-benefit analysis must be performed to determine the optimal capacity of the storage systems. In this paper, the maximum/rated capacity of battery storage is considered as 0.5 MW, and the rated capacity of the supercapacitor is 1.5 MW. In this case, it is assumed that the charge/discharge efficiencies of the battery storage is 0.9 and that of the supercapacitor is 0.95. The minimum and maximum SOC of both the battery storage and supercapacitor are considered to be 10% and 100%, respectively [34,35].

In this case, the objective function (i.e., Equation (11)) consists of all the terms except for the second and third terms, as this case doesn't consist of the wind and solar PV energy systems. The state of charge of the battery and supercapacitor is depicted in Figure 6.

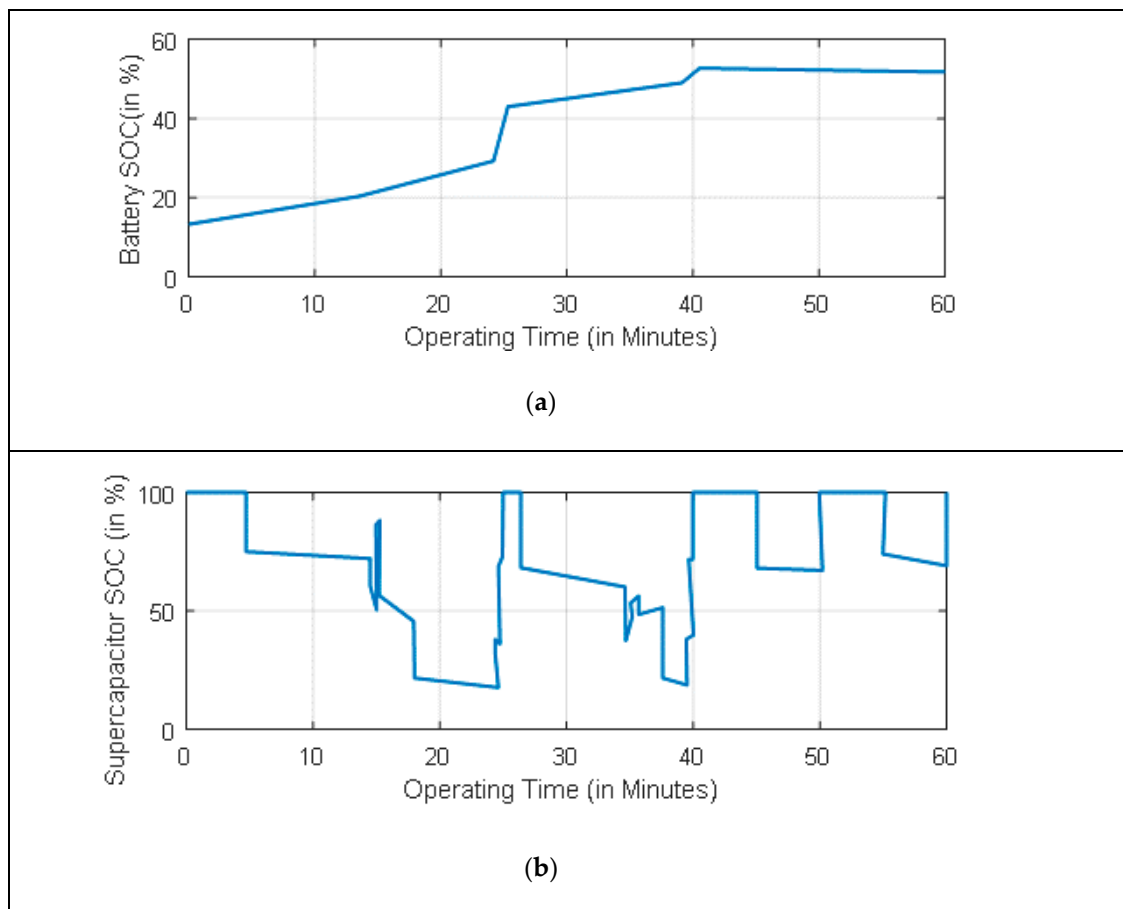


Figure 6. Data of energy storage system: (a) State of charge (SOC) of battery; (b) SOC of supercapacitor.

The total power absorbed from the grid and the energy obtained from battery and supercapacitor are 4.247 MWh, 0.421 MWh, and 0.293 MWh, respectively. The optimum operating cost obtained in this case is \$290.22 per hour, which is 10.96% less than the cost obtained from the base case (i.e., case study 1), and 5.41% less than that obtained from case study 2. The computational time required for this case is 19.05 s.

5.4. Case Study 4

In this case, the railroad operation is performed by considering the RERs (i.e., wind and solar PV powers) and hybrid energy storage systems. Here, the objective function consists of all the terms of Equation (11), and it is solved using the DEA. The total power absorbed from the grid, wind, and solar PV power generations, and the energy obtained from the battery and supercapacitor in this case are 3.862 MWh, 1.160 MWh, 0.816 MWh, 0.382 MWh, and 0.241 MWh, respectively. The optimum operating cost obtained in this case is \$283.40 per hour, which is 13.05% less than the cost obtained from the base case (i.e., case study 1), 7.63% less than that of case study 2, and 2.35% less than that of case study 3. This is because by considering the high amount of electrical energy available from the integration of RERs, hybrid energy storage and regenerative braking have reduced the total operating cost of the railroad electrical system. The computational time required for this case is 19.22 s. From the results, it can also be observed that the proper utilization of hybrid energy storage systems is beneficial for regenerative braking and handling the intermittent nature of RERs.

From the simulation results, it can be observed that the proposed optimization model allows the current energy flow to be optimized, while keeping future stages in account, and this process is termed model predictive control (MPC) [36,37]. Considering the simulation results obtained from the above four case studies, it can be concluded that by operating the railroad electrical systems in the multi-source environment considering RERs, regenerative braking, and hybrid storage systems, the amount of electrical energy returned to the main utility grid increased, which resulted in considerable savings in the total operating cost of the system.

6. Conclusions

This paper has presented an approach for the efficient operation of railroad electrical systems in the multi-source environment considering the renewable energy resources (i.e., wind and solar PV energy systems), regenerative braking, and hybrid energy storage systems. In this paper, battery storages and supercapacitors are considered as a hybrid energy storage system. An AC optimal power flow (AC-OPF) problem is formulated by optimizing the total operating cost of the system. The uncertainties involved due to the incorporation of wind and solar PV powers has been handled using the probability distribution functions. This optimal scheduling problem has been solved by using the differential evolution algorithm (DEA). Simulations are performed on four different case studies, which show the effectiveness of the proposed approach. The results from the presented case studies show that by operating the railroad system with renewable energy resources (RERs), regenerative braking, and hybrid storage systems has achieved cost savings of 13.05% when compared to the railroad system without RERs, regenerative braking, and hybrid energy storage systems. Solving the proposed optimal scheduling problem of a railroad electrical system by using a robust and stochastic variant of model predictive control (MPC) is a scope for future work.

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Nomenclature

Nomenclature	Define
C_G	Cost of active power generation (in \$/MWh).
P_{Gi}	Active power output/generation from the network at the i th node.
C_W	Cost of wind power generation (in \$/MWh).
P_{Wj}	Wind power output at the j th node.
C_S	Cost of solar photovoltaic (PV) power generation (in \$/MWh).
P_{Sk}	Solar power output at the k th node.
C_{sp}	Selling price of excess power (in \$/MWh).
$P_{ex,l}$	Available excess power at the l th node.
$p_{B,b}^{ch}$	Charging power of storage battery at the b th node.
$p_{B,b}^{disch}$	Discharging power of storage battery at the b th node.
$p_{SC,u}^{ch}$	Charging power of supercapacitor at the u th node.
$p_{SC,u}^{disch}$	Discharging power of supercapacitor at the u th node.
p_{Gi}^{min}	Power returned to the grid.
p_{Gi}^{max}	Power consumed from the grid.
P_T, Q_T	Active and reactive power demand of the T th train.
P_{Di}, Q_{Di}	Active and reactive power demand at the i th node.
S_{Li}	Line flow of the i th line.
S_{Li}^{max}	Thermal limit of the i th line.

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