INTRODUCTION

Due to the penetration of various types of energy resources to supply different types of energy demand, the interaction between all of the energy carriers is inevitable.\textsuperscript{1} Regarding the energy hub concept, an organized framework can achieve to supply different loads from various energy sources in an efficient economic way.\textsuperscript{2} Therefore, integrating energy resources is essential not only to reduce the cost of energy procurement but also to improve the efficiency of the energy systems.\textsuperscript{3} In this regard, to supply the ERS energy consumption, utilizing RERs besides the RBE is taken into consideration recently.\textsuperscript{4,5}

Regenerative braking denotes an energy recovery mechanism during braking that converts the kinetic energy into electrical form.\textsuperscript{6} The converted energy is called regenerative braking energy that can use to supply the load of ERS,\textsuperscript{7} sell back to the electric grid,\textsuperscript{8} or store in ES.\textsuperscript{9}

Regarding the energy management of electric railway systems, quite a few researches have been done. Aiming to minimize energy consumption and maximize RER utilization, reference\textsuperscript{10} proposes a novel mathematical approach...
based on matrix and differential control theory for optimal control strategy of trains' trajectory, considering the profile and plan of the route besides utilizing the RBE. In Ref. [11], hierarchical energy management proposed a multitrain railway transport system in the presence of ES to maximize economic benefits. To coordinate renewable energy resources with energy storage systems in a railway power substation, a fuzzy logic supervision strategy presented in Ref. [12]. The authors of Ref. [13] presented a methodology for the optimal operation of ERS to investigate the RBE capabilities beside RERs to achieve economic and energy savings. Besides, the uncertain behavior of RERs is considered through the scenario tree approach. The authors of Ref. [14] proposed an energy management model for a smart railway station, in which the RBE and PV power generation used to supply the electric load of the railway station. However, the uncertainty related to the available RBE and exerting DRP ignored. Considering the PV power generation and ES, Ref. [15] presents an energy management model for traction power systems to reduce the daily operating costs. Nevertheless, in this study, the uncertainty related to the PV power generation and the available RBE has neglected.

Recently, over the energy hub system topic, there has been much research on the optimal operation of multi-energy systems along with employing new elements. To coordinate the operation of multiple energy systems, Ref. [16] presents a mixed-integer linear programming (MILP) model to minimize the daily operation cost, considering the DRP. To investigate vehicle to grid impact on customer payment costs minimization, Ref. [17] presents a residential energy hub model including plug-in hybrid electric vehicles, CHP, PV panels, and ES. The authors of Ref. [18] presented a multi-objective optimization model for a residential energy hub operation to minimize the purchased energy cost. Further, the contribution of the customer to CO$_2$, NO$_x$, and SO$_x$ emission is taken into account. The emission problem of the energy hub, besides economic performance, is investigated in Ref. [19]. Also, the weighted sum approach was used to solve the presented MILP model. The authors of Ref. [20] proposed an energy management model to study the effects of ESs and RERs on the optimal operating strategy for a residential energy hub in a competitive electricity market. The authors of Ref. [21] presented a day-ahead scheduling procedure for a microgrid with the aim of operation and emission cost minimization, in which different operating strategies for the integrated CHP units have been studied. In the presence of electricity and heating markets, Ref. [22] presents a risk-based stochastic scheduling model for energy hub systems in which the downside risk constraints are employed to manage the risk of uncertain parameters. The author of Ref. [23] proposes a bi-objective optimal operation model, considering economic and emission aspects, in order to assess the impacts of a real-time-based DRP for an energy hub system. However, the uncertainty related to the RERs has been ignored. Reference [24] has studied different feeding schemes of electrical railway systems and proposed a useful road map for future railway power supply systems considering the concept of the energy hub. Table 1 contains the summary of literature review.

Based on smart grid concept, a smart railway system can exchange electricity with the electric grid and utilize renewable energy resources to supply its demand. In addition, as discussed in the literature review, there is a research gap about the energy management of smart railway stations from an energy hub point of view, where different types of a station's demands, including power, heat, and cooling demand, are considered. This paper tries to address this research gap. Thus, a stochastic bi-objective model for energy management of a smart railway station and its dependent commercial buildings based on the energy hub system architecture is presented. Also, the recovered energy obtain from the regenerative braking (RB) during train deceleration is utilized to supply the load of EHS. Furthermore, to improve the flexibility of the system, a real-time rate of DRP is applied. Besides, the uncertainty related to the photovoltaic power generation and the power obtained from RB are considered. The main contributions of this paper are as follows:

- An EHS structure has been proposed for a smart railway station and its related building.
- A bi-objective model has been presented for the economic-environmental operation of the proposed EHS, unlike Refs. [11-15] that just consider the economic aspect.
- The thermal and electrical load of a smart railway station has been considered, unlike Ref. [14] that considers just power load.
- The uncertainty related to available RBE has been considered through a generation and reduction scenario technique which is more accurate compared to the methodology of Refs. [11-15].
- A real-time DRP has been implemented to evaluate the economic-environmental benefits as well as peak shaving capability for the proposed EHS, unlike Ref. [14].

The rest of this paper is formed as follows: The architecture of the proposed energy hub system and the proposed bi-objective model are presented in Section 2. Section 3 introduces the case studies and reports the simulation results. Finally, Section 4 includes a summarized conclusion.

### 2 | SYSTEM MODEL

Figure 1 shows the schematic of presumed SRS. As can be seen, the SRS consists of PV, ES, RBE, and the load spectrum of the SRS, which can exchange power with the electric
| Reference | Solution approach | Objective function | Loads | Uncertain phenomenon | Considered DRP |
|-----------|-------------------|--------------------|-------|-----------------------|----------------|
| 11        | Deterministic model Single-objective optimization | ✓ | x | ☑ | ☑ |
| 12        | Deterministic model Two-level optimization | ✓ | x | ☑ | ☑ |
| 13        | Stochastic model Single-objective optimization | ✓ | x | ☑ | ☑ |
| 14        | Stochastic model Single-objective optimization | ✓ | x | ☑ | ☑ |
| 15        | Deterministic model Single-objective optimization | ✓ | x | ☑ | ☑ |
| 16        | Deterministic model Single-objective optimization | ✓ | x | ☑ | ☑ |
| 17        | Deterministic model Single-objective optimization | ✓ | x | ☑ | ☑ |
| 18        | Deterministic model Multi-objective optimization | ✓ | ✓ | ☑ | ☑ |
| 19        | Deterministic model Multi-objective optimization | ✓ | ✓ | ☑ | ☑ |
| 20        | Deterministic model Multi-objective optimization | ✓ | x | ☑ | ☑ |
| 21        | Deterministic model Single-objective optimization | ✓ | x | ☑ | ☑ |
| 22        | Stochastic model Single-objective optimization | ✓ | x | ☑ | ☑ |
| 23        | Deterministic model Multi-objective optimization | ✓ | ✓ | ☑ | ☑ |
| This paper | Stochastic model Multi-objective optimization | ✓ | ✓ | ☑ | ☑ |
Also, RBE obtained from trains is utilized to provide a portion of a load of SRS. It should mention that the proposed energy hub system supplies the internal demand of the smart railway station plus the demand for its commercial-related building, including power, heating, and cooling demand. Also, it is assumed that the energy consumed by trains supplied via traction substations and the issues regarding the supply of the traction load is out of the scope of this paper. The spectrum of the load of the SRS consists of escalator, elevator, lighting, heating, air conditioning, and ventilation. Figure 2 depicts the schematic of integrated SRS and the subenergy hub and relevant connections in the proposed
EHS. By linking the subenergy hubs, loads of EHS, including power, heating, and cooling demand, will be provided. Also, rooftop PV modules are employed as a renewable energy resource. Since the power obtained from the RBE might be more than the demand of the EHS in time interval \( t \), an ES is used to store the surplus energy. Moreover, conversion devices, including electrical absorption, gas boiler, and gas turbine, and storage systems (ES, HS, and CS), are employed to supply the EHS demands reliably.

### 2.1 Modeling train motion

In order to calculate the accessible RBE, the train motion simulated based on the vehicle characteristic and route data.\(^{26-29}\) Figure 3 depicts the simulation process of the RBE calculation. The composition of forces imposed on the train determines the movement of it, regarding Newton’s mechanical laws. \( F_{\text{train}} \) in Equation (1) denotes the major forces which imposed on the train during motion, including the force generated by traction motors \( (F_{\text{tr}}) \), basic resistance force \( (F_{\text{bg}}) \), gradient resistance force \( (F_{\text{rg}}) \), and curve resistance force \( (F_{\text{rc}}) \). By Equation (2), the train power \( (P_{\text{tr}}) \) can be calculated at each moment.

\[
F_{\text{train}} = F_{\text{tr}} - F_{\text{rg}} - F_{\text{rc}} \quad (1)
\]

\[
P_{\text{tr}} = \frac{\left( M \frac{dv}{dt} + F_{\text{train}} \right)}{\eta_{\text{gt}}} + P_{a} \quad (2)
\]

In (2), \( M, v, \eta_{\text{gt}}, \eta_{\text{tr}}, \) and \( P_{a} \) define the effective mass of train, train velocity, gearboxs efficiency, traction motor efficiency, and auxiliary loads of train, respectively. According to (1) and (2), uncertain parameters, including the train mass and the traction/braking effort, affected the power of the train directly.\(^{30,31}\)

### 2.2 Modeling PV power generation

To estimate the output power of the PV module, the Equations (3)-(7) are utilized. Also, \( \text{Sor}_{r,s} \) and \( \theta_{am}^{r,s} \) denote solar radiation and ambient temperature at hour \( r \) and scenario \( s \), respectively.\(^{32}\)

\[
\theta_{r,s} = \theta_{am}^{r,s} + \text{Sor}_{r,s} \times \left( \frac{N^{0,5} - 20}{0.8} \right) \quad (3)
\]

\[
P_{PV}^{r,s} = \text{Sor}_{r,s} [P_{sc}^{r,s} + K^{r,s}(\theta_{r,s} - 25)] \quad (4)
\]

\[
V_{PV}^{r,s} = V_{OC}^{r,s} - K^{r,s} \times \theta_{r,s} \quad (5)
\]

\[
P_{PV}^{r,s} = N_{PV}^{r,s} \times F_{PV}^{r,s} \times I_{PV}^{r,s} \quad (6)
\]

\[
F_{PV}^{r,s} = \frac{V_{MPP}^{r,s} \times I_{MPP}^{r,s}}{V_{OC}^{r,s} \times F_{SC}^{r,s}} \quad (7)
\]

Additionally, the PV power generation depends on the solar irradiance and ambient temperature as well as the specification of the module itself, for instance, the short circuit current \( (I_{SC}) \), fill factor \( (FF) \), current/voltage temperature coefficient \( (K^{r,s}, K^{r,s}) \), and the number of PV module \( (N_{PV}^{r,s}) \).

### 2.3 The mathematical formulation of the energy hub system

#### 2.3.1 Objective functions

The first objective function of the proposed model \( (\Phi_{1}) \) is shown in (8). The cost of exchanging energy with external energy resources, including the cost of exchanging power with the electricity grid and the cost of purchased gas from the gas network, is considered.

\[
\min \Phi_{1} = \sum_{r} \sum_{w} \sum_{t} \pi_{r} \cdot \pi_{w} \cdot \left( P_{w,\text{grid}}^{g,r,s} \cdot \lambda_{\text{el}}^{r,s} + P_{w,\text{gas}}^{g,r,s} \cdot \lambda_{\text{gas}}^{r,s} \right) \cdot \Delta t \quad (8)
\]

\( \pi_{r} \) and \( \pi_{w} \) are the probability occurrence of scenarios related to the PV generation and the available RBE, respectively. Moreover, \( P_{w,\text{grid}}^{g,r,s} \) is a decision variable while the positive value denotes purchasing, and the negative value denotes selling electricity to the electric grid in time interval \( t \) and scenarios \( r \) and \( w \).

The reduction of carbon emission for environmental purposes is considered as the second objective \( (\Phi_{2}) \). Equation (9) shows the equivalent of carbon emission of the consumed energy to supply the demand of the EHS.

\[
\min \Phi_{2} = \sum_{r} \sum_{w} \sum_{t} \pi_{r} \cdot \pi_{w} \cdot \left( P_{w,\text{grid}}^{g,r,s} \cdot \beta_{\text{el}}^{r,s} + P_{w,\text{gas}}^{g,r,s} \cdot \beta_{\text{gas}}^{r,s} \right) \cdot \Delta t \quad (9)
\]

Also, \( P_{w,\text{gas}}^{g,r,s} \) is a free variable that denotes the purchased gas from the gas network in time interval \( t \) and scenarios \( r \) and \( w \).

#### 2.3.2 The constraint of subhub energy balance

The power demand of the energy hub system can be provided by five sources, as shown on the left-hand side of Equation (10).

\[
P_{r,w,t}^{\text{el,d}} = P_{r,w,t}^{\text{el},\text{grid}} + P_{r,w,t}^{\text{el},\text{PV}} + P_{r,w,t}^{\text{el},\text{RB},\text{in}} + P_{r,w,t}^{\text{el},\text{DRP}} + P_{r,w,t}^{\text{el},\text{ES}} \quad (10)
\]
As illustrated in Equation (11), the heating demand of EHS can be provided by the GB, the GT, and the HS.

\[
H_{r,w,d}^{gb} + H_{r,w,d}^{gl}n_{he} + P_{r,w,d}^{hs,d} = H_{r,w,d}^{pc} + P_{r,w,d}^{hs,i} + P_{r,w,d}^{hl} \tag{11}
\]

The cooling discharged from the ice storage, besides the cooling produced via the electrical chiller and the absorption chiller, provides the cooling demand. The cooling balance constraint is illustrated in (12).

\[
C_{r,w,d}^{sc} + C_{r,w,d}^{cs}n_{he} + P_{r,w,d}^{cs,d} = P_{r,w,d}^{cl} \tag{12}
\]

### 2.3.3 Technical constraints for energy storage devices

For the stable operation of energy storages, a set of time-dependent constraints in each scenario should meet; as expressed in Equation (13), existing energy in energy storage is dependent on untaken energy in the last time interval \((t-1)\), the amount of energy storage loss, and charging or discharging power at each time interval \(t\). The charging or discharging power of the electricity storage is restricted by Equations (14) and (15), respectively. The maximum and minimum energy allowed to be stored in electricity storage is presented in (14) and (15), respectively. The maximum and minimum energy allowed to be stored in electricity storage is guaranteed by Equation (16). Moreover, the equality of initial and final conditions of the electricity storage is guaranteed by Equation (17). Also, the same constraints for heat and cooling storages are expressed in (18) to (27).

#### a. Electricity storage

\[
SOE_{r,w,d}^{es} = SOE_{r,w,d-1}^{es} - (1 - \delta_{es}) + \left( \frac{P_{r,w,d}^{es,d}}{\eta_{es,d}} + P_{r,w,d}^{es,c} \cdot \eta_{es,c} \right) \cdot \Delta t \tag{13}
\]

\[
0 \leq P_{r,w,d}^{es,c} \leq P_{r,w,d}^{max,es,c} \cdot u_{r,w,d}^{es} \tag{14}
\]

\[
0 \leq P_{r,w,d}^{es,d} \leq P_{r,w,d}^{max,es,d} \cdot (1 - u_{r,w,d}^{es}) \tag{15}
\]

\[
E_{r,w,t}^{min,es} \leq SOE_{r,w,d}^{es} \leq E_{r,w,t}^{max,es} \tag{16}
\]

\[
SOE_{r,w,d,initial}^{es} = SOE_{r,w,d,end}^{es} \tag{17}
\]

#### b. Heating storage

\[
SOE_{r,w,d}^{hs} = SOE_{r,w,d-1}^{hs} - (1 - \delta_{hs}) + \left( \frac{P_{r,w,d}^{hs,d}}{\eta_{hs,d}} + P_{r,w,d}^{hs,c} \cdot \eta_{hs,c} \right) \cdot \Delta t \tag{18}
\]

\[
0 \leq P_{r,w,d}^{hs,c} \leq P_{r,w,d}^{max,hs,c} \cdot u_{r,w,d}^{hs} \tag{19}
\]

\[
0 \leq P_{r,w,d}^{hs,d} \leq P_{r,w,d}^{max,hs,d} \cdot u_{r,w,d}^{hs} \tag{20}
\]

\[
E_{r,w,t}^{min,hs} \leq SOE_{r,w,d}^{hs} \leq E_{r,w,t}^{max,hs} \tag{21}
\]

\[
SOE_{r,w,d,initial}^{hs} = SOE_{r,w,d,end}^{hs} \tag{22}
\]

#### c. Cooling storage

\[
SOE_{r,w,d}^{cs} = SOE_{r,w,d-1}^{cs} + \left( \frac{P_{r,w,d}^{cs,d}}{\eta_{cs,d}} + P_{r,w,d}^{cs,c} \cdot \eta_{cs,c} \right) \cdot \Delta t \tag{23}
\]

\[
0 \leq P_{r,w,d}^{cs,c} \leq P_{r,w,d}^{max,cs,c} \cdot u_{r,w,d}^{cs} \tag{24}
\]

\[
0 \leq P_{r,w,d}^{cs,d} \leq P_{r,w,d}^{max,cs,d} \cdot (1 - u_{r,w,d}^{cs}) \tag{25}
\]

\[
E_{r,w,t}^{min,cs} \leq SOE_{r,w,d}^{cs} \leq E_{r,w,t}^{max,cs} \tag{26}
\]

\[
SOE_{r,w,d,initial}^{cs} = SOE_{r,w,d,end}^{cs} \tag{27}
\]

### 2.3.4 Technical constraints of the performances of devices

The power transactions between the electric grid and the EHS are presumed to be bidirectional. The exchange of power is carried through a transformer. The energy exchange constraints with the external sources are expressed via (28) to (30).

\[
P_{r,w,t}^{in} = P_{r,w,t}^{ge} \cdot \eta_{tran} \tag{28}
\]

\[
-P_{r,w,t}^{eg} \leq P_{r,w,t}^{ge} \leq P_{r,w,t}^{max,ge} \tag{29}
\]

\[
0 \leq P_{r,w,t}^{gas} \leq P_{r,w,t}^{max,gas} \tag{30}
\]

Consuming gas, the GT generates power and coproducts heat, which is modeled by Equations (31) and (32). The other portion of input gas is consumed by a GB to produce heat, Equation (33). So the total gas consumption is expressed by Equation (34). Also, other constraints related to the operation of the GB and the AB are illustrated in (35) to (37).

\[
P_{r,w,t}^{gb} = P_{r,w,t}^{ge} \cdot \eta_{ge} \tag{31}
\]

\[
H_{r,w,t}^{gl} = P_{r,w,t}^{ge} \cdot \eta_{gh-gl} \tag{32}
\]
The ice storage air conditioner is employed to meet cooling demand besides the electric chiller. The ISC can reduce the peak of power demand by shifting a portion of power consumption to off-peak hours.\textsuperscript{34} During off-peak hours, the ISC stores ice and works in the ice-making mode. The stored ice in the ice storage tank will be melt in the ice-melting mode to supply the cooling demand at on-peak hours. In addition, it cannot work at the same time in ice-melting and ice-making modes. The capacity for making ice by the chiller defined as \((38)\).

\[
P_{\text{ice},\text{c}} = P_{\text{ice},\text{c}} \cdot \text{COP}_{\text{ice}} \quad (38)
\]

The electric chiller generates cooling energy by consuming power, while the absorption chiller converts heat energy to cooling energy. These conversions can be formulated mathematically as Equations (39) and (40). Also, constraints (41) and (42) ensure the proper operation of the cooling hub. Specifically, they limit the \(P_{\text{c,ice}}\) and \(P_{\text{c,ac}}\) to their maximum amounts.

\[
C_{\text{c,ice}} = P_{\text{c,ice}} \cdot \text{COP}_{\text{c,ice}} \quad (39)
\]

\[
C_{\text{c,ac}} = H_{\text{c,ac}} \cdot \text{COP}_{\text{c,ac}} \quad (40)
\]

\[
0 \leq P_{\text{c,ice}} \leq P_{\text{c,ice}}^{\text{max}} \quad (41)
\]

\[
0 \leq P_{\text{c,ac}} \leq P_{\text{c,ac}}^{\text{max}} \quad (42)
\]

As mentioned, the recovered energy during the braking of trains utilized to supply the power demand of EHS. Also, some amount of recovered energy inevitably is wasted due to the efficiency and capacity of conversion devices.\textsuperscript{34,35} In order to limit the variable \(P_{\text{RBE},\text{c}}\) from taking higher values than the available RB power and considering the efficiency of the conversion process, Equations (43)-(45) are employed.

\[
0 \leq P_{\text{RBE},\text{c}} \leq P_{\text{RB},\text{c}} \quad (43)
\]

\[
P_{\text{RBE},\text{c}} = P_{\text{RBE},\text{c}} \cdot \text{COP}_{\text{RBE},\text{c}} \quad (34)
\]

\[
0 \leq P_{\text{gl}} \leq P_{\text{max}} \quad (35)
\]

\[
0 \leq H_{\text{gb}} \leq H_{\text{gb}}^{\text{max}} \quad (36)
\]

\[
0 \leq H_{\text{ac}} \leq H_{\text{ac}}^{\text{max}} \quad (37)
\]

\[
P_{\text{pl}} = \frac{W_{\text{d}}}{24} \quad (47)
\]

\[
\gamma_t = \frac{P_{\text{pl}}}{P_{\text{av}}} \quad (48)
\]

\[
\lambda_t^{\text{RTP}} = \gamma_t \cdot \lambda_t^{\text{TOU}} \quad (49)
\]

As the proposed bi-objective problem has two conflicting objectives, the \(\varepsilon\)-constraint method is employed to solve it.\textsuperscript{40-43} In the \(\varepsilon\)-constraint method, for a two objective function problem, the main objective \((\Phi_1)\) is optimized while the other objective \((\Phi_2)\) is considered as a constraint and limited by some allowable amount \((\varepsilon)\).\textsuperscript{41} Therefore, the bi-objective problem changes into a single-objective optimization problem, which solves every time with a different amount of \(\varepsilon\). Also, the entire variation of \(\varepsilon\) considered from \(\Phi_2^{\text{min}}\) to \(\Phi_2^{\text{max}}\). Finally, a
Pareto front is gained by optimal solutions that are obtained from solving the problem frequently.

Furthermore, to select the best possible solution from the obtained Pareto front, the fuzzy satisfying approach is implemented. In this method, each objective function has its fuzzy membership that mapped its values to the interval \([0, 1]\). The employed linear membership function is illustrated in (52) for the \(n\)-th solution of the \(i\)-th objective function.\(^{41,42}\)

\[
q^n_i = \begin{cases} 
1 & \Phi^n_i < \Phi^\text{min}_i \\
\frac{\Phi^n_i - \Phi^\text{max}_i}{\Phi^\text{min}_i - \Phi^\text{max}_i} & \Phi^\text{min}_i \leq \Phi^n_i \leq \Phi^\text{max}_i \\
0 & \Phi^n_i > \Phi^\text{max}_i 
\end{cases} 
\] (52)

\(q^n_i\) reflects the optimality of the \(n\)-th solution of the \(i\)-th objective function. Also, \(\Phi^\text{max}_i\) and \(\Phi^\text{min}_i\) are the maximum and minimum values of the obtained solutions of the \(i\)-th objective function for the multi-objective problem. By the min-max criterion described in Ref. [43], the best compromise solution can be selected from the entire Pareto optimal set through (53).

\[
\text{BCS} = \max_i \left( \min_n (q^n_i) \right) 
\] (53)

For the sake of clarity, by choosing the maximum value of the weakest membership functions, the best compromise solution will be detected.

### Table 2 Description of case studies

| Case studies | Regenerative braking energy | PV | Electricity storage | Heating storage | Cooling storage | DRP |
|--------------|----------------------------|----|---------------------|----------------|----------------|-----|
| Case 1       | -                          | -  | -                   | -              | -              | -   |
| Case 2       | -                          | -  | -                   | -              | -              | ✓   |
| Case 3       | -                          | -  | ✓                   | -              | -              | -   |
| Case 4       | ✓                          | ✓  | -                   | -              | -              | ✓   |
| Case 5       | -                          | ✓  | ✓                   | ✓              | -              | -   |
| Case 6       | ✓                          | ✓  | ✓                   | ✓              | ✓              | -   |
| Case 7       | ✓                          | ✓  | ✓                   | ✓              | ✓              | ✓   |

Note: The sign ✓ denotes that the EHS contains the device or the DRP.

### Table 3 The parameters of energy storage systems

| Parameter | Value | Parameter | Value | Parameter | Value |
|-----------|-------|-----------|-------|-----------|-------|
| \(E^\text{min}_{es}\) [kWh] | 200   | \(E^\text{max}_{cs}\) [kWh] | 120   | \(E^\text{min}_{hs}\) [kWh] | 360   |
| \(E^\text{max}_{es}\) [kWh] | 1000  | \(E^\text{max}_{cs}\) [kWh] | 600   | \(E^\text{max}_{hs}\) [kWh] | 1800  |
| \(P^\text{max}_{es,c}\) [kW] | 720   | \(P^\text{max}_{cs,c}\) [kW] | 240   | \(P^\text{max}_{hs,c}\) [kW] | 720   |
| \(P^\text{max}_{es,d}\) [kW] | 900   | \(P^\text{max}_{cs,d}\) [kW] | 300   | \(P^\text{max}_{hs,d}\) [kW] | 900   |
| \(\eta_{es,c}\) | 0.95  | \(\eta_{cs,c}\) | 0.97  | \(\eta_{hs,c}\) | 0.98  |
| \(\eta_{es,d}\) | 0.96  | \(\eta_{cs,d}\) | 0.95  | \(\eta_{hs,d}\) | 0.98  |
| \(\delta_{es}\) | 0.01  | \(\delta_{cs}\) | 0.02  | \(\delta_{hs}\) | 0.02  |
Four PV generation (r set) and three RBE scenarios (w set) are considered, thus yielding twelve possible scenarios used to model the optimization problem in a stochastic manner.

Regarding the uncertain behavior of the PV generation, the following steps have been taken. According to the historical hourly data of the solar irradiation and the ambient temperature for Tehran city, the Monte Carlo method employed to generate 100 PV generation scenarios each season. Also, it assumed that the occurrence probability of scenarios is equal. The number of scenarios affects the computational burden of the optimization problem directly. Thus, the backward reduction technique is employed to reduce the

| Parameter | Value | Parameter | Value | Parameter | Value |
|-----------|-------|-----------|-------|-----------|-------|
| $H_{gb}^{\max}$ [kW] | 800 | $P_{RBE}^{\max}$ [kW] | 100 | $\mu_g$ [kg/kWh] | 0.23 |
| $H_{ac}^{\max}$ [kW] | 1000 | $\eta_{ge}$ | 0.3 | $\rho_a$ [kg/kWh] | 0.972 |
| $P_{max}^{e}$ [kW] | 1000 | $\eta_{gb}$ | 0.9 | COP_{ac} | 3.5 |
| $P_{gas}^{\max}$ [kW] | 1500 | $\eta_{gb}$ | 0.4 | COP_{ec} | 4 |
| $P_{en}^{\max}$ [kW] | 1000 | $\eta_{en}$ | 0.98 | COP_{ac} | 1.2 |
| $P_{ac}^{\max}$ [kW] | 200 | $\eta_{ac}$ | 0.7 | - | - |
| $P_{ice}^{\max}$ [kW] | 100 | $\eta_{con}$ | 0.98 | - | - |

**FIGURE 4** The EHS power, cooling, and heating demand during a day

**FIGURE 5** The reduced PV power profile scenarios

**TABLE 4** The data of EHS assets
number of scenarios. Finally, four scenarios with new occurrence probability selected between 400 generated scenarios in a year (4 seasons * 100 scenarios in each season). The profiles of PV power generation gained after converting the irradiation and temperature scenarios according to the “PV model” section. Moreover, PV panel’s specifications in Ref. [49] were used. The occurrence probability of each four scenarios illustrated in Table 5.

The price of electricity in the time-of-use scheme and the calculated real-time pricing scheme with the mentioned DRP model are shown in Figure 6. By comparing the price of electricity in these pricing schemes, it can be observed that the price is higher in on-peak periods (9:00-14:00 and 18:00-21:00) in the real-time pricing scheme, and it is lower in off-peak periods (1:00-8:00) compare to the time-of-use scheme. Consequently, the SRS will respond to the price signal by changing the pattern of its power consumption.

Due to the increase in energy prices during on-peak, peak load shaving is essential for ERSs regarding the economic aspect. On the other side, due to the significant amount of consumed energy by ERSs, peak load shaving can make the external electricity grid operation smooth. According to implementing the DRP, the power demand profiles obtained by changing the demand price elasticity coefficient ($E$) are depicted in Figure 7. Also, Table 6 contains the detailed characteristics of these power profiles, including peak, valley, and load factors. As can be seen, increasing the absolute value of $E$ leads to a flatter power load profile, effected by shifting a portion of the load from the peak to the valley of load that can bring economic improvement for the EHS. Specifically, if $E$ equals −0.5, the peak load at 20:00 decreased about 300 kW or 19.8%, besides the valley of load increased about 150 kW or 22% at 2:00. Therefore, the load factor of the power demand profile increased, and it can conclude that the

### Table 5 The four reduced scenarios with corresponding probability

| Scenarios | $r_1$ | $r_2$ | $r_3$ | $r_4$ | Probability |
|-----------|-------|-------|-------|-------|-------------|
| $w_1$     | .024  | .166  | .34   | .47   | .333        |
| $w_2$     | .33   | .333  | .334  |       |             |

![Figure 6](https://via.placeholder.com/150)

**Figure 6** The price of electricity in the TOU and RTP schemes

![Figure 7](https://via.placeholder.com/150)

**Figure 7** The power demand profiles for different values of $E$
characteristics of the power demand profile improved after exerting the DRP. Also, it should be noted that the amounts of the percent reduction in the peak row of Table 6 are being compared with $E = 0$.

A portion of train mass consists of the mass of passengers. The number of passengers is an uncertain parameter. Also, as mentioned before, train mass affects the available RBE. Therefore, by changing the number of passengers and the

| Elasticity coefficient | $E = 0$ | $E = -0.1$ | $E = -0.2$ | $E = -0.3$ | $E = 0.4$ | $E = -0.5$ |
|------------------------|---------|------------|------------|------------|------------|------------|
| Peak                   |         |            |            |            |            |            |
| Amount [kW]            | 1480    | 1421.1     | 1362.2     | 1303.3     | 1244.4     | 1185.5     |
| Reduction [%]          | -       | 3.8        | 7.9        | 12         | 15.9       | 19.8       |
| Valley [kW]            | 650     | 675.0      | 700.1      | 725.2      | 750.3      | 775.4      |
| Load factor [%]        | 71.5    | 74.1       | 76.9       | 80.0       | 83.4       | 87.0       |

**FIGURE 8** The generated RB power profile scenarios

**FIGURE 9** Pareto front selected solutions for case studies
related timetable of the trains each hour, three different power profiles obtained for the available RBE, which are shown in Figure 8. It should mention that the occurring probabilities of these three scenarios are assumed equal.

Due to the conflict between the economic and environmental objectives of the model, by employing the ε-constraint method, the optimal Pareto solution fronts are obtained for seven case studies, which are depicted in Figure 9. Also, the

| Case study | Amount [\$] | Reduction | Percentage [%] | Amount [kg] | Reduction | Percentage [%] |
|------------|-------------|-----------|----------------|-------------|-----------|----------------|
| Case 1     | 10 989.7    | -         | -              | 24 220      | -         | -              |
| Case 2     | 10 470.8    | 518.9     | 4.7            | 23 589      | 631       | 2.6            |
| Case 3     | 10 787.7    | 202       | 1.8            | 23 631      | 589       | 2.4            |
| Case 4     | 10 203      | 786.7     | 7.2            | 21 900      | 2320      | 9.5            |
| Case 5     | 10 011.2    | 978.5     | 8.9            | 23 116      | 1104      | 4.5            |
| Case 6     | 9945.5      | 1044.2    | 9.5            | 22 018      | 2202      | 9              |
| Case 7     | 9426.6      | 1563.1    | 14.2           | 21 387      | 2833      | 11.6           |

**TABLE 7** Comparison between the operation cost and carbon emission of the case studies

**FIGURE 10** Optimal hourly scheduling of the power hub in cases 6 and 7
selected solutions individually are shown with a different color (yellow points).

The daily operating cost and carbon emission of the selected optimal solutions in different cases are summarized in Table 7. The amounts of the percent reduction are given in columns 3 and 5 of Table 7 compared with case 1. Comparing the selected solutions in pair case 1 and case 2 as well as case 6 and case 7, it can be observed that utilizing the DRP caused a 4.7% and 2.6% reduction in the daily operation cost and carbon emission, respectively, which shows the effectiveness of the DRP to bring economic-environmental benefit for the EHS.

Comparing the results of case 3 and case 1 shows that by utilizing PV generation as renewable energy resources, the operation cost and carbon emission decreased 202 $ and 589 kg, respectively. Also, comparing case 4 with case 3, shows that by utilizing the RBE to supply the EHS demand instead of wasting it as heat through braking resistor, the operation cost and carbon emission improved about 5.3% and 7.1%, respectively. Furthermore, an interesting comparison between the results of cases 4 and 6 illustrates that by utilizing energy storage units, the operation cost decreased about 2.4% while the carbon emission increased by 0.5%. It is worth mentioning that the demand price elasticity coefficient is assumed −0.5.

Moreover, the proposed model is compared with Ref. [14], as one of the similar existing energy management models for smart railway stations, in order to evaluate their performance. Reference [14] just has considered the power load of a station. Also, the RBE is used to supply the station's demand and its stochastic behavior is neglected. However, the uncertainty associated with the initial state of energy of the ESS and PV power generation is considered. Furthermore, the proposed models in this paper and Ref. [14] have a similar methodology and employed scenario-based programming managing the SRS energy flow. Comparing the mentioned method with other existing analytical methodologies, for instance, 11-15 reveals that the model has enough accuracy applying in the

**FIGURE 11** Optimal hourly scheduling of the heating hub in cases 6 and 7
energy management field. In addition, through a comprehensive energy management model for electric railway systems, considering all types of demands, with the aim of cost and emission reduction, an optimal economic-environmental operation can be achieved, which is not addressed by the previous studies.\textsuperscript{11-15}

3.1 Analysis of energy flow

As mentioned, the scenario-based stochastic approach used to analyze the operation of the proposed EHS. Hence, the results presented for scenario $r_2w_j$, which has the lowest PV and RB power generation among the scenarios. The optimal dispatch results of selected solutions in case 6 and case 7 in each subenergy hub illustrated in Figures 10-12. Also, for Figures 10-12, the upper side of diagrams with positive values denotes the entered energy to the subhub, and the negative values in the lower part show the amount of energy that flows out from the subhub.

For all scenarios, the energy consumption and generation at the subenergy sections should be in balance at each time interval. As shown in Figure 10, during hours 1:00 to 5:00, when the electricity price is relatively low, the electric grid mainly provided power for the EHS except at 4:00 in case 7. After implementing the DRP in case 7, at 4:00 a part of the power demand and whole heat demand is provided by the GT. During hours 1:00 to 5:00 in case 6, the demanded heat is provided by the GB and HS. Also, in hours 6:00-23:00, due to the relatively high price of electricity and the capability of the GT to cogenerate heat and power, the heat load is usually provided by the GT. The power obtained from the RBE and PV meets a portion of the power demand or sells back to the electric grid when the generated power is surplus aiming at the operating cost reduction. During the peak hours 18:00 to 21:00, purchased power is zero at 19:00, besides at 20:00, the EHS sold power to the electricity grid in case 7. Comparing with case 6, the EHS purchased power from the electricity grid during the same period, which

\textbf{FIGURE 12} Optimal hourly scheduling of the cooling hub in cases 6 and 7
indicates the effectiveness of the DRP to decrease the tension upon the electric grid, plus it brings economic benefit for the EHS. Furthermore, the power obtained from the RBE, the ES, and PV is the alternative suppliers for the power demand of the EHS.

At the heating section, from 8:00 to 11:00 and 18:00 to 19:00, the HS is an auxiliary supplier to provide heating demand besides the GT when it works at maximum capacity. Also, from 1:00 to 5:00, the GB mainly supplied the heating demand. Comparing the GT and the GB to provide the heating demand, the GB has a smaller role.

For the cooling subhub, the EC works almost all the time in both cases, except at 10:00 and 11:00 when the purchasing power is zero, and at 19:00, which the electricity price is relatively high. During these periods, the AB and the CS provide the cooling demand. In hours 9:00 and 10:00, there are some differences between case 7 and case 6. In case 7 at 9:00, the ISC works in melting ice mode and supplies a portion of the cooling demand, while in case 6, the AB provides the cooling energy as an auxiliary supplier. At 10:00, the CS beside the AB employed to supply the cooling demand in case 7, while in case 6, the CS used to provide the cooling load, lonely.

**FIGURE 13** State of energy storage in scenario $r_2w_1$
The state of energy for the ES, the HS, and the CS depicted in Figure 13. According to the energy price, the ES stored energy and worked in charging mode when the electricity price is low, while it supplied the power demand in peak load hours. Also, all of the energy storage systems have the same state of energy in cases 7 and 6, due to the low generation of PV and the available RBE in scenario $r_2w_1$; except at 10:00–11:00 for the HS and at 11:00 for the CS, which are different in cases 7 and 6 as mentioned previously. Also, the ISC provided a portion of the cooling demand by melting the ice stored in the ice storage tank during off-peak hours, specifically from 12:00 to 15:00. Furthermore, according to Table 7, the energy storage devices improved the operating cost and increased the carbon emission, comparing cases 4 and 6.

### 3.2 Evaluating pricing schemes

This part evaluates the impact of different pricing schemes on the operation of the SRS, including RTP, TOU, and fixed price. The flat price is assumed 20 $/kWh, and it is fixed during the day. Also, the two other price signals are illustrated in Figure 6. Table 8 contains the obtained optimal results under each pricing scheme. By comparing the outcomes, it can be concluded that the RTP scheme is beneficial for the SRS from an economic-emission perspective. Furthermore, the energy storage units play a much important role in managing the energy flow of the SRS under the RTP scheme than the other pricing schemes. Specifically, the total charged and discharged power of all energy storage units reduced by about 14% under the TOU scheme. Moreover, under RTP the energy storage units stored more energy observing the average of stored energy which can improve the reliability of the SRS operation.

### 4 CONCLUSION

An energy hub architecture for a smart railway station integrated with dependent commercial buildings proposed in this article. Based on the proposed architecture, an optimal operation problem is formulated stochastically utilizing mixed-integer linear programming to decrease the operation cost and the carbon emission. The simulation results show a significant reduction in the operation cost and the carbon emission for the proposed EHS in different case studies. For instance, exerting the DRP solely reduced the operation cost by 4.7% and improved 2.6% of the carbon emission. Also, by utilizing the recovered energy to meet the demand of the proposed EHS, the operation cost and the carbon emission reduced by 14.2% and 11.6%, respectively.

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