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Evaluation of the Operational Efficiency and Energy Efficiency of Rail Transit in China's Megacities Using a DEA Model

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Abstract: To date, along with the rapid development of urban rail transit (URT) in China, the evaluation of operational efficiency and energy efficiency has become one of the most important topics. However, the extant literature regarding the efficiency of URT at the line level and considering carbon emissions is limited. To fill the gap, an evaluation model based on slacks-based measure (SBM) data envelopment analysis (DEA) is proposed to measure the efficiencies, which is applied to 61 URT lines in China's four megacities. The findings are summarized as follows: (1) The average operational efficiency and energy efficiency of URT lines are low, and both have great room for improvement. (2) There are significant disparities in the efficiency of URT lines in the case cities. For instance, the average operational efficiency of URT lines in Guangzhou is higher than that of other cities, while the average energy efficiency of URT lines in Shanghai is higher than that of other cities. (3) The URT lines operated by state-owned enterprises have higher average operational efficiency, while the lines operated by joint ventures have higher average energy efficiency. Finally, some suggestions are provided to improve the efficiencies.

Keywords: urban rail transit; operational efficiency; energy efficiency; carbon emission; data envelopment analysis

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1. Introduction

Over the past two decades, urban rail transit (URT) has rapidly developed to mitigate traffic congestion in China's megacities [1]. According to statistics, by the end of 2021, 50 cities on the Chinese mainland operated 283 URT lines with a total length of 9206.8 km [2]. Compared with other means of public transportation, URT is faster, more frequent, and punctual, which is an important part of urban public transportation. Due to the rapid increase in modernization and the advance of rail transit planning in urban agglomerations, URT has a larger potential development space in China. Improving the operational efficiency of URT makes a great impact on economic and social activities. Operational efficiency evaluation can identify sources of inefficiency and improve URT's operation, which has become one of the most important investigation topics [3,4].

In the literature, URT is usually considered a complex system with multiple inputs (e.g., train, line, station, and energy) to provide transit services and thereby produce multiple outputs (e.g., passenger kilometers, passenger volume, and train kilometers). The efficiency evaluation of public transport is always investigated by comparing multiple inputs and outputs comprehensively [5–8]. In this study, the operational efficiency of URT can be defined as the conversion efficiency between the input system and the output system. Multi-criteria decision analysis (MCDA) methods can be used to comprehensively evaluate alternatives [9–11]. However, different MCDA methods often produce contradictory results when comparing, and decisionmakers may obtain different decisions even using the same criteria weights and criterial evaluations of variants [11]. As one of the non-parametric approaches, data envelopment analysis (DEA) has the advantage of having no pre-determined weights, which is applicable in estimating the relative efficiency of decision-making units (DMUs) with multiple inputs and outputs. Since first proposed by Charnes et al. [12], DEA has been successfully and widely applied to measure efficiency in the public transport sector, such as railways (e.g., [13–15]), highway bus transit (e.g., [16–18]), shipping and ports (e.g., [19–21]), and airlines and airports (e.g., [22–24]).

In terms of the efficiency of URT, it can be measured at different levels, such as the city level and the company level. In this sense, Karlaftis [19] used the DEA model to measure the efficiency and effectiveness of 256 US URT systems, and the results showed that efficiency is positively correlated with effectiveness. Jain et al. [25] applied DEA to explore the relationship between technical efficiency and ownership structure for 15 global URT systems and found that privatization directly and positively impacts efficiency. Qin et al. [26] adopted a slacks-based multi-stage network DEA to assess the efficiency of 17 URT systems in China in 2012 and found that lower average overall efficiency is more related to inefficiencies in the earning stage and construction stage. Tsai et al. [27] used DEA to measure the efficiency of 20 international URT systems from 2009 to 2011 and suggested that the number of stations and population density impact efficiency significantly. Costa et al. [28] utilized DEA to compute the efficiency of four URT systems in Portugal from 2009 to 2018 and explored the impact of the ownership model on efficiency. The findings indicated that privately managed firms were more efficient than public firms. Although the above studies made great progress, estimation at the city or company level cannot identify the efficiency of specific lines or provide deeper insight into the improvement of efficiency at the line level.

To the best of our knowledge, studies on the efficiency of URT at the line level are scarce. Kang et al. [29] developed a mixed network DEA model and a hybrid two-stage network DEA model to explore the efficiency of two metro systems, including six lines in Taipei, and found that the efficiency results between the two models differed significantly. Le et al. [30] used the DEA model to measure the operational efficiency, cost efficiency, and revenue efficiency of 18 URT lines in the Tokyo Metropolitan Area in 2017. The results indicated that the in-vehicle congestion rate can be a reflection of the service quality in the operational efficiency measurement. Unfortunately, these two studies did not consider carbon emissions in the efficiency evaluation process. Due to growing environmental concerns, carbon emissions are considered an undesirable output in efficiency estimations in the transportation sector [31–33]. An efficiency measurement without considering carbon emissions may lead to imprecise operational efficiency results, which leaves a research gap.

In addition, with the increase in URT mileage, the corresponding energy consumption is also rising. The measurement of URT's energy efficiency can help operators save electricity and reduce operating costs and carbon emissions. However, while there are many studies on energy efficiency in the transportation sector [7,33–35], few works focus on the URT field. To the best of our knowledge, two studies are closely related to this topic. Xiao et al. [36] applied the DEA model to evaluate the energy efficiency of URT in Beijing Metro Lines 5 and 15 and the Batong Line without considering carbon emissions in the evaluation. To et al. [37] used the dimensional indicator to discuss the energy efficiency of Hong Kong's mass transit railway over the period from 2008–2017 and found that the energy efficiency was between 0.076 and 0.093 kWh per passenger–km and CO_2 emissions were between 0.055–0.071 kg per passenger–km. Notably, the energy efficiency in this study was similar to the energy intensity. The efficiency evaluation did not consider other inputs and outputs and may not provide significant implications. Hence, there exists another gap related to energy efficiency in URT lines, which needs to be explored.

To fill the gaps, this study aims to estimate operational efficiency and energy efficiency considering CO_2 emissions for URT at the line level, which is the novelty of this paper. To achieve this, an evaluation model based on the slacks-based measure (SBM) is developed to assess operational efficiency and energy efficiency synchronously. Furthermore, a method of detecting the improvement potentials of inputs and outputs is proposed. Then, this study applies the proposed model to the URT lines in China's four megacities (Beijing, Shanghai, Guangzhou, and Shenzhen).

In summary, the contributions of this study are listed as follows. First, this study measures the operational efficiency and energy efficiency of the URT in consideration of CO_2 emissions at the line level, which is a step further than previous studies have taken on undesirable outputs. Second, the proposed model can evaluate operational efficiency and energy efficiency simultaneously and provide more precise results. Third, an empirical study of China's 61 URT lines in four major cities verifies the effectiveness of the proposed model. This micro-level research may enrich the theoretical literature and provide new management enlightenment for efficiency improvement in URT operation.

The remainder of this paper is structured as follows. The methodology is presented in Section 2. Section 3 presents the results, and Section 4 provides discussions. Finally, Section 5 illustrates the conclusions and limitations.

2. Methodology

To clearly describe the evaluation method, the input and output variables and the operation process of the URT system are introduced first. Then, the SBM model is developed to measure the operational efficiency of URT lines. Furthermore, a measurement for energy efficiency is proposed.

2.1. Input and Output Variables and Operation Process

Generally, a URT system is invested in by enterprises to provide travel services for citizens. Its operation process is shown in Figure 1. According to previous studies, line mileage, station, train, and energy are indispensable resources for transportation services [19,26,29,38,39]. Hence, these four resources are considered input variables in the operation process. Passenger transport volume and revenue passenger kilometers are taken as the two desirable output variables, while energy-related CO_2 emission is considered one undesirable output variable.

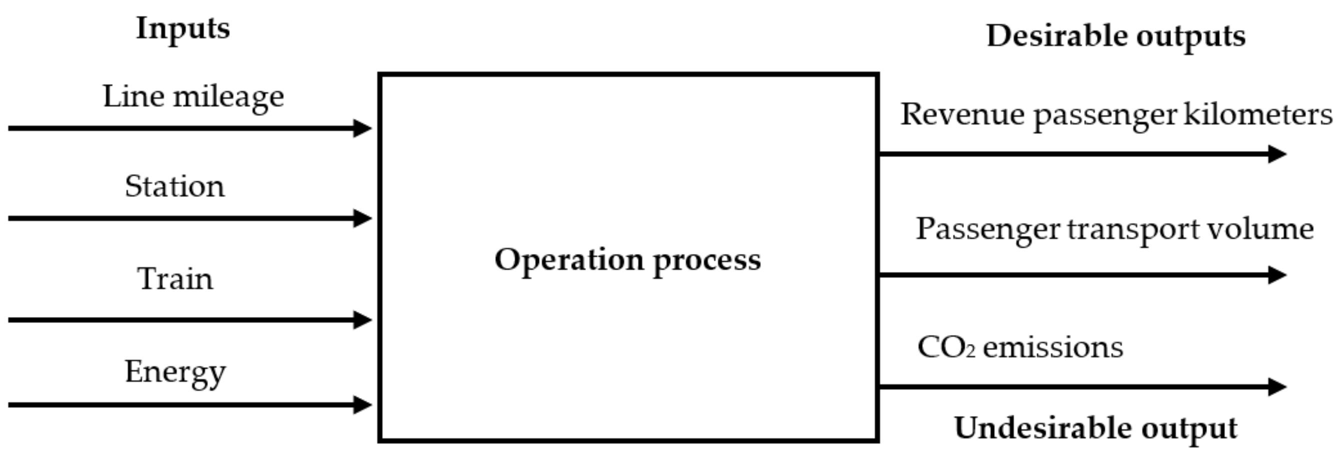

Figure 1. The operation process of a URT system.

2.2. Efficiency Evaluation Model Based on SBM-DEA

This study aims to measure the operational efficiency and energy efficiency of Chinese URT lines with the SBM model. As a non-radial DEA approach, the SBM model directly captures each "input excess" and "output shortfall" to identify the inefficiency of DMUs from an overall perspective [40]. Therefore, the SBM model has been widely used to evaluate the efficiency of public transportation systems, such as by Zhang et al. [41], Chu et al. [42], and Tavassoli et al. [43].

Suppose that there are n DMUs, which represent the URT lines, denoted by DMU_j ($j = 1, 2, \ldots, n$). Each DMU utilizes line mileage (XL), station (XD), train (XT), and energy

(XE) and then produces passenger transport volume (YP), revenue passenger kilometers (YR), and CO_2 emissions (YC). The evaluation model for the operational efficiency of the URT line based on SBM can be expressed as follows:

$$\begin{aligned}
\theta_i = \min & \frac{1-\frac{1}{4}\left(\frac{s_l^-}{XL_i}+\frac{s_d^-}{XD_i}+\frac{s_t^-}{XT_i}+\frac{s_e^-}{XE_i}\right)}{1+\frac{1}{3}\left(\frac{s_p^+}{YP_i}+\frac{s_r^+}{YR_i}+\frac{s_c^-}{YC_i}\right)} \\
\text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j XL_j + s_l^- = XL_i, \\
& \sum_{j=1}^{n} \lambda_j XD_j + s_d^- = XD_i, \\
& \sum_{j=1}^{n} \lambda_j XT_j + s_t^- = XT_i, \\
& \sum_{j=1}^{n} \lambda_j XE_j + s_e^- = XE_i, \\
& \sum_{j=1}^{n} \lambda_j YP_j - s_p^+ = YP_i, \\
& \sum_{j=1}^{n} \lambda_j YR_j - s_r^+ = YR_i, \\
& \sum_{j=1}^{n} \lambda_j YC_j + s_c^- = YC_i, \\
& \sum_{j=1}^{n} \lambda_j = 1, \\
& \lambda_j, s_l^-, s_d^-, s_t^-, s_e^-, s_p^+, s_r^+, s_c^- \geq 0,\ j = 1,2,\ldots,n.
\end{aligned} \tag{1}$$

In Model (1), θ_i represents the operational performance score; s_l^-, s_d^-, s_t^-, s_e^-, s_p^+, s_r^+, and s_c^- are slacks of line mileage, station, train, energy, passenger transport volume, revenue passenger kilometers, and CO_2 emission, respectively, representing either the excess of the input or the shortfall of the output. λ_j expresses the participation degree of each DMU in constructing the production frontier. Note that Model (1) is non-linear. To simplify the calculation, a linear form is transformed following the proposed method by Tone [40] as follows:

$$\begin{aligned}
\theta_i = & \min\left(t - \frac{1}{4}\left(\frac{S_l^-}{XL_i} + \frac{S_d^-}{XD_i} + \frac{S_t^-}{XT_i} + \frac{S_e^-}{XE_i}\right)\right) \\
\text{s.t.} \quad & t + \frac{1}{3}\left(\frac{S_p^+}{YP_i} + \frac{S_r^+}{YR_i} + \frac{S_c^-}{YC_i}\right) = 1 \\
& \sum_{j=1}^{n} \eta_j XL_j + S_l^- = tXL_i, \\
& \sum_{j=1}^{n} \eta_j XD_j + S_d^- = tXD_i, \\
& \sum_{j=1}^{n} \eta_j XT_j + S_t^- = tXT_i, \\
& \sum_{j=1}^{n} \eta_j XE_j + S_e^- = tXE_i, \\
& \sum_{j=1}^{n} \eta_j YP_j - S_p^+ = tYP_i, \\
& \sum_{j=1}^{n} \eta_j YR_j - S_r^+ = tYR_i, \\
& \sum_{j=1}^{n} \eta_j YC_j + S_c^- = tYC_i, \\
& \sum_{j=1}^{n} \eta_j = t, \\
& \eta_j, S_l^-, S_d^-, S_t^-, S_e^-, S_p^+, S_r^+, S_c^- \geq 0, j = 1,2,\ldots,n.
\end{aligned} \tag{2}$$

The variables in Model (1) undergo the following transformations in Model (2): $\lambda t = \eta$, $ts_l^- = S_l^-, ts_d^- = S_d^-, ts_t^- = S_t^-, ts_e^- = S_e^-, ts_p^+ = S_p^+, ts_r^+ = S_r^+, ts_c^- = S_c^-$. The optimal η_j^*, S_l^{-*}, S_d^{-*}, S_t^{-*}, S_e^{-*}, S_p^{+*}, S_r^{+*}, S_c^{-*}, and t^* are measured for operational performance, θ_i^*. If $\theta_i^* = 1$ and all optimal slacks are equivalent to 0, the performance is efficient; otherwise, it is inefficient. Moreover, if a larger performance score of a DMU is obtained, it indicates that this DMU operates better than other DMUs.

In DEA theory, the projected point on the production frontier is the optimal target for each inefficient DMU to pursue. Hence, the DEA method can be used to set the optimization targets of inputs and outputs to improve performance. The target energy expresses a minimum level of energy input to achieve optimal operational performance. Naturally, the target energy input can be obtained with the following equation:

$$TE_i = \sum_{j=1}^{n} \lambda_j XE_j \tag{3}$$

Hence, energy efficiency, ρ_i, is defined as the ratio of target energy to its actual consumed energy in this study. It is can be expressed as follows:

$$\rho_i = \frac{TE_i}{XE_i} \tag{4}$$

For ease of reading, the formulas for calculating the improvement potentials of variables are provided in Appendix A.

3. Empirical Study

3.1. Data Source

As for the empirical analysis, the datasets from the URT lines were collected from the yearbook of the China Urban Rail Transit Almanac 2021, which is an annual report released by the China Association of Urban Rail Transit. In total, 61 URT lines from Beijing, Shanghai, Guangzhou, and Shenzhen were considered for analysis. As shown in Figure 2, Beijing, Shanghai, Guangzhou, and Shenzhen are the top four cities in terms of economic strength on the Chinese mainland. Each city has a population of more than 10 million and an urban rail network of hundreds of kilometers. A large number of people take urban rail transit for their daily travel. Overall, data on line mileage, station, train, energy, passenger transport volume, and revenue passenger kilometers were collected from the aforementioned yearbook. While there are no official statistics on CO_2 emissions, we calculated the carbon emission based on energy consumption and the regional grid carbon emission factor in 2019 following the approach of Yu et al. [44]. Descriptive statistics are shown in Table 1.

Table 1. Descriptive Statistics [1].

Variable	Line Mileage (km)	Station	Train	Energy (10^4 kwh)	Passenger Transport Volume (10^4 PT)	Revenue Passenger Kilometers (10^4 PK)	CO_2 (10^4 tons)
Max	81.40	45.00	116.00	29,997.00	56,139.00	499,058.00	24.49
Min	3.90	2.00	4.00	1046.00	180.10	1891.00	0.84
Mean	37.85	22.39	50.38	12,243.28	14,769.75	129,951.56	10.26
SD	15.63	9.96	26.70	6813.24	11,363.46	100,773.41	5.69

[1] PT and PK are short for person-time and passenger kilometers, respectively.

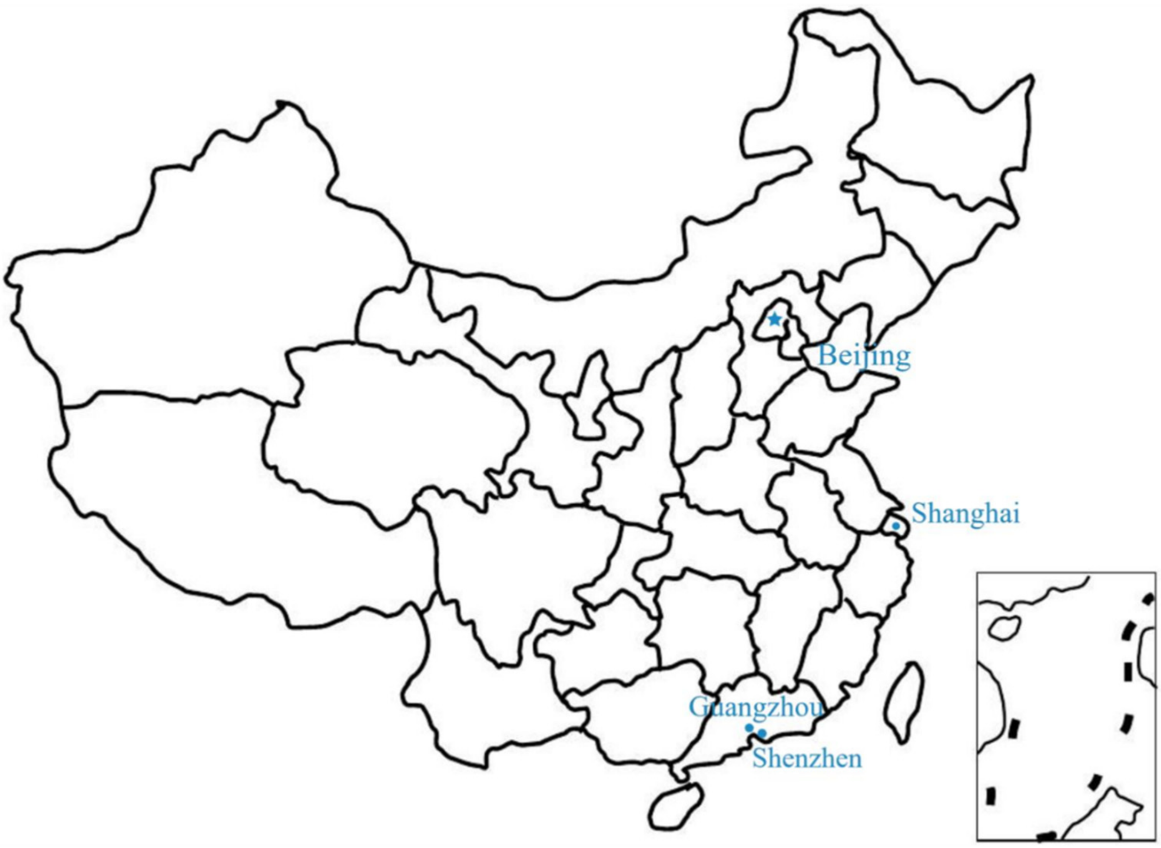

Figure 2. Four megacities in mainland China.

3.2. Efficiency Results

Table 2 and Figure 3 show the efficiency results at the line level and the city level, respectively. As can be seen from Table 2, the average operational efficiency is 0.5634. Overall, the average room for URT lines to improve operational efficiencies is 43.66%. From a line angle, it can be seen that of the operational efficiencies of the 61 observed URT lines, 10 of which are evaluated as being an efficient level, another 15 lines are over the average level, and 36 lines are under the average level. There is a significant difference between URT lines in efficiency. From a city angle, Figure 3 suggests that the average operational efficiency of the URT lines in Guangzhou (0.6453) tops the list. The average operational efficiency of URT lines in Shanghai (0.5921) is higher than the average level, while those of the URT lines in Beijing (0.5054) and Shenzhen (0.5157) are slightly lower than the average level. That is to say, in terms of operational efficiency, there is a slight difference between URT lines at the city level. The reason might be that these megacities are similar in terms of their large population and high economic development level.

Table 2. The efficiency of the URT systems in case cities.

City	Line Name	Operational Efficiency	Energy Efficiency
Beijing	BJ-Line 1	0.4978	0.6264
	BJ-Line 2	0.6100	0.9338
	BJ-Line 4	0.5534	0.7648
	BJ-Line 5	0.6363	0.7953
	BJ-Line 6	0.4514	0.5669
	BJ-Line 7	0.2978	0.3621
	BJ-Line 8	0.2583	0.3937
	BJ-Line 9	0.6827	0.8589
	BJ-Line 10	0.5011	0.6816

Table 2. *Cont.*

City	Line Name	Operational Efficiency	Energy Efficiency
	BJ-Line 13	1.0000	1.0000
	BJ-Line 15	0.4755	0.7136
	BJ-Line 16	0.2337	1.0000
	BJ-Ba Tong Line	0.5034	0.7695
	BJ-Changping Line	0.4839	0.7098
	BJ-Fangshan Line	0.3897	0.7360
	BJ-Capital Airport Express	1.0000	1.0000
	BJ-Yizhuang Line	0.5210	0.7726
	BJ-Line S1	0.4582	0.8313
	BJ-Yanfang Line	0.1703	1.0000
	Daxing Airport Express	0.3835	0.8522
Shanghai	SH-Line 1	0.7284	0.8102
	SH-Line 2	0.6271	0.6593
	SH-Line 3	0.4579	0.6813
	SH-Line 4	1.0000	1.0000
	SH-Line 5	0.3441	0.5530
	SH-Line 6	0.4503	0.8257
	SH-Line 7	0.4973	0.7020
	SH-Line 8	0.6560	0.8782
	SH-Line 9	0.6037	0.9204
	SH-Line 10	0.5341	0.7536
	SH-Line 11	0.5230	0.8840
	SH-Line 12	0.4086	0.6036
	SH-Line 13	0.4006	0.5204
	SH-Line 16	0.4028	0.8354
	SH-Line 17	0.4325	0.6074
	SH-Pujiang Line	1.0000	1.0000
	SH-Maglev Line	1.0000	1.0000
Guangzhou	GZ-Line 1	1.0000	1.0000
	GZ-Line 2	1.0000	1.0000
	GZ-Line 3	1.0000	1.0000
	GZ-Line 4	0.3907	0.5833
	GZ-Line 5	0.7386	0.7233
	GZ-Line 6	0.5449	0.7320
	GZ-Line 7	0.6451	0.6479
	GZ-Line 8	0.6409	1.0000
	GZ-Line 9	0.4179	0.7522
	GZ-Line 13	0.4449	0.6373
	GZ-Line 14	0.3138	0.4875
	GZ-Line 21	0.3319	0.4218
	GZ-APM Line	1.0000	1.0000
	GZ-Guangfo Line	0.5657	0.7845
Shenzhen	SZ-Line 1	0.5881	0.6987
	SZ-Line 2	0.3099	0.5008
	SZ-Line 3	0.5907	0.7982
	SZ-Line 4	0.6102	0.8385
	SZ-Line 5	0.6361	0.7252
	SZ-Line 6	0.3345	0.7195
	SZ-Line 7	0.4164	0.5595
	SZ-Line 9	0.3310	0.3948
	SZ-Line 10	0.3398	1.0000
	SZ-Line 11	1.0000	1.0000
	Average	0.5634	0.7641

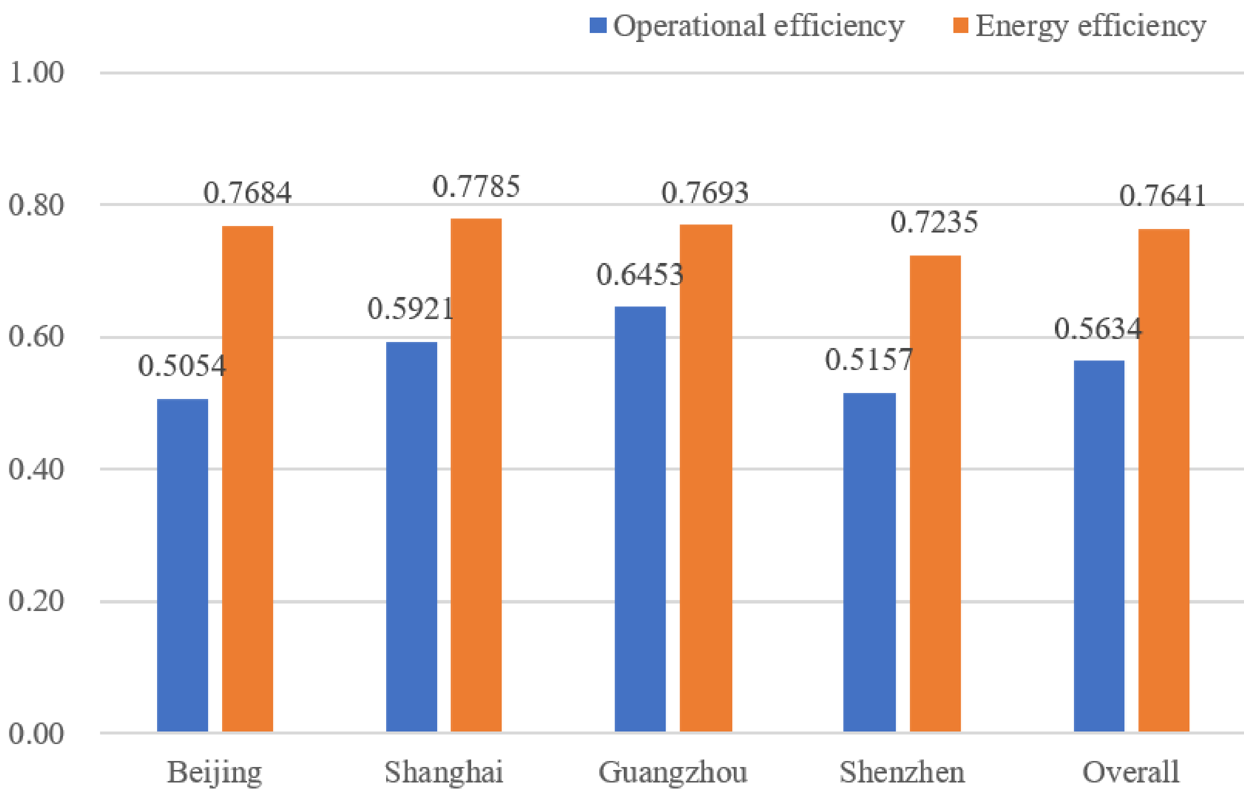

Figure 3. The average efficiency of the URT systems in case cities.

In particular, it can be seen that around five-sixths of the URT lines are inefficient. In Beijing, the operational efficiencies of 2 out of 20 observed URT lines are efficient, another 3 lines are over the overall average level, and 15 lines are under the overall average level. In Shanghai, the operational efficiencies of 3 out of 17 observed URT lines are efficient, another 4 lines are over the overall average level, and 10 lines are below the overall average level. In Guangzhou, the operational efficiencies of 4 out of 14 observed URT lines are efficient, another 4 lines are over the overall average level, and 6 lines are below the overall average level. In Shenzhen, the operational efficiencies of 1 out of 10 observed URT lines are efficient, another 4 lines are over the overall average level, and 5 lines are below the overall average level. Obviously, the operational efficiencies of most URT lines need to be improved further, as they are underperforming. For instance, the operational efficiency of Beijing Line 8 is 0.2583, suggesting that the operational efficiency can be improved by 30.51% and 76.17% to reach the overall average and optimal level, respectively. In a similar vein, in other case cities, the operational efficiencies of SH-Line 5 (0.3441), GZ-Line 14 (0.3138), and SZ-Line 2 (0.3099) can be improved by 65.59%, 68.62%, and 69.01%, respectively, to reach the optimal level. These lines with poor performance should make great efforts to improve operational efficiency to reach the overall average level first and then pursue a higher efficiency.

Similar results are also observed in energy efficiency. Overall, the average energy efficiency of the URT lines is 0.7641. That is to say, the URT lines are recommended to improve their energy efficiency by 23.59% on average to reach the optimal energy utilization level. From a line perspective, it can be found that of the energy efficiencies of the 61 observed URT lines, 14 of which are evaluated as an efficient level, another 17 lines are over the average level, and 30 lines are under the average level. There is a great disparity among URT lines in energy efficiency. From a city perspective, Figure 3 suggests that the average energy efficiency of the URT lines in Shanghai (0.7785) tops the list. The average operational efficiencies of URT lines in Guangzhou (0.7693) and Beijing (0.7684) are higher than the average level, while those of the URT lines in Shenzhen (0.7235) are lower than the average performance level. That being said, there is no significant difference in energy efficiency between URT lines at the city level. It might be that these cities have developed URT in similar periods, with a mixture of new and old facilities and equipment in the lines.

Additionally, the results illustrate that the energy efficiency of most URT lines is inefficient. In Beijing, the operational efficiencies of 2 out of 20 observed URT lines are efficient, another 10 lines are over the overall average level, and 8 lines are below the overall average level. In Shanghai, the operational efficiencies of 3 out of 17 observed URT lines are efficient, another 6 lines are over the overall average level, and 8 lines are below the overall average level. In Guangzhou, the operational efficiencies of 4 out of 14 observed URT lines are efficient, another 2 lines are over the overall average level, and 6 lines are below the overall average level. In Shenzhen, the operational efficiencies of 2 out of 10 observed URT lines are efficient, another 2 lines are over the overall average level, and 6 lines are below the overall average level. Obviously, the energy efficiencies of most URT lines need to be improved further, as they are underperforming. For instance, the energy efficiency of some of the cases is much lower than the average level (e.g., the energy efficiency of BJ-Line 7 is 0.3621), suggesting that the operational efficiencies can be improved by 40.2% and 63.79% to reach the overall average and optimal level respectively. In a similar vein, in other case cities, the operational efficiencies of SH-Line 7 (0.3092), GZ-Line 21 (0.4218), and SZ-Line 9 (0.3974) can be improved by 69.08%, 57.82%, and 59.36%, respectively, to reach the optimal level. These lines with worse performance should make more efforts to improve operational efficiency to reach the overall average level first and then pursue a higher efficiency.

In other words, the efficiency of the energy consumption of these URT systems is optimized. Furthermore, of the 61 observed URT systems, 31 of them are above the average level; the energy efficiency of 14 observed URT systems is optimized. For those higher than the average level, the energy efficiency of 3 out of 20 URT systems in Beijing is optimized; the energy efficiency in 11 URT systems is above the average level). Likewise, 3 out of 17 URT systems in Shanghai are optimized in terms of energy efficiency; nine URT systems in Shanghai perform better than the average level in terms of energy efficiency. Meanwhile, in Guangzhou, 5 out of 14 URT systems reach the ideal level of energy consumption efficiency; the energy efficiency of nine URT systems in Guangzhou is higher than the average level. In Shenzhen, 2 out of 10 URT systems are fully optimized; the energy utilization level of four URT systems in Shenzhen is higher than the average level. In these cases, some of them are close to the optimal level. For example, the energy efficiency of BJ-Line 2 is 0.9338, which demonstrates a significant potential to reach the ideal energy consumption efficiency. In other cases, some of them are under the average level of energy consumption efficiency. For instance, the energy efficiency of the BJ-Fangshan Line is 0.736, which is close to the average value. In other words, there is a potential to further improve performance beyond the average level. Furthermore, the energy efficiency of some of the cases is much lower than the average level (e.g., the energy efficiency of SZ-Line 9 is 0.3948).

In addition to the efficiencies across cities, Table 3 reports a comparison of the efficiencies of URT lines operated by joint ventures and state-owned enterprises. The average operational efficiency of the state-owned lines (0.5684) is higher than that of the joint lines (0.4658). Specifically, there are three lines operated by joint ventures (i.e., BJ-Line 4, BJ-Yanfang Line, and SZ-Line 4). Only the operational efficiency of SZ-Line 4 (0.6102) is higher than the average level.

Table 3. The average efficiency of the URT systems in case cities.

Type	Operational Efficiency	Energy Efficiency
Joint venture	0.4658	0.8678
State-owned enterprise	0.5684	0.7587
Overall	0.5634	0.7641

Regarding energy efficiency, the average energy efficiency of URT lines operated by joint ventures is 0.8678, which is higher than the overall energy efficiency (0.7641), while the average energy efficiency of URT lines operated by state-owned enterprises (0.7587) is slightly lower than the overall value. The reason may be that the joint-owned lines were built in a more recent period, with more new energy-saving technologies. To sum up, state-owned enterprises are better at improving operational efficiency, while joint ventures are more concentrated on energy efficiency. This may be due to the difference between the two ownership models. In this sense, operators are encouraged to learn from each other's management and technology advantages so as to maximize their efficiencies.

3.3. Improvement Analysis

As shown in Table 4 and Figure 4, the improvement potentials of inputs and outputs for the URT lines and case cities are presented. As mentioned in the previous methodology section, line mileage and station are not discussed in the adjustment analysis, as they cannot be easily changed after they are built.

Table 4. The improvement values of the URT systems in case cities.

City	Line Name	Train	Energy (10^4 kwh)	Passenger Transport Volume (10^4 PT)	Revenue Passenger Kilometers (10^4 PK)	CO_2 (10^4 tons)
Beijing	BJ-Line 1	−56.63% (−39.64)	−37.36% (−5503.57)	0.00% (0.00)	0.00% (0.00)	−46.57% (−6.46)
	BJ-Line 2	−51.20% (−25.60)	−6.62% (−593.65)	0.00% (0.00)	67.99% (55475.85)	−20.27% (−1.71)
	BJ-Line 4	−57.68% (−49.60)	−23.52% (−4126.99)	10.42% (2489.35)	0.00% (0.00)	−34.70% (−5.73)
	BJ-Line 5	−52.85% (−32.24)	−20.47% (−2571.82)	0.00% (0.00)	0.00% (0.00)	−32.09% (−3.80)
	BJ-Line 6	−50.63% (−42.53)	−43.31% (−11258.96)	35.91% (7660.91)	0.00% (0.00)	−51.62% (−12.64)
	BJ-Line 7	−71.66% (−48.73)	−63.79% (−10938.69)	0.00% (0.00)	5.20% (4802.56)	−69.08% (−11.16)
	BJ-Line 8	−80.87% (−89.77)	−60.63% (−8717.98)	5.76% (566.00)	0.00% (0.00)	−66.46% (−9.00)
	BJ-Line 9	−50.70% (−19.26)	−14.11% (−982.93)	0.00% (0.00)	30.79% (21903.56)	−26.66% (−1.75)
	BJ-Line 10	−60.80% (−70.53)	−31.84% (−8025.87)	0.00% (0.00)	0.00% (0.00)	−41.80% (−9.93)
	BJ-Line 15	−32.19% (−10.94)	−28.64% (−3132.13)	67.37% (6002.66)	0.00% (0.00)	−39.07% (−4.02)
	BJ-Line 16	−43.35% (−16.47)	0.00% (−0.00)	322.69% (8138.21)	259.66% (65798.21)	−14.82% (−0.81)
	BJ-Ba Tong Line	−53.53% (−19.81)	−23.05% (−1153.24)	21.12% (1163.62)	0.00% (0.00)	−34.55% (−1.63)
	BJ-Changping Line	−37.77% (−12.09)	−29.02% (−2072.49)	64.82% (3608.44)	0.00% (0.00)	−39.56% (−2.66)
	BJ-Fangshan Line	−59.57% (−26.21)	−26.40% (−1476.97)	78.65% (3180.23)	0.00% (0.00)	−37.38% (−1.97)
	BJ-Yizhuang Line	−41.39% (−9.52)	−22.74% (−1110.60)	40.54% (1926.50)	0.00% (0.00)	−34.03% (−1.57)
	BJ-Line S1	0.00% (−0.00)	−16.87% (−455.47)	119.00% (1161.69)	178.52% (9366.26)	−29.63% (−0.75)
	BJ-Yanfang Line	−30.64% (−4.90)	0.00% (−0.00)	579.51% (3000.11)	520.04% (20791.87)	−14.81% (−0.31)
	Daxing airport express	−46.73% (−5.61)	−14.78% (−1055.11)	273.57% (1595.43)	8.57% (1805.91)	−28.15% (−1.89)
Shanghai	SH-Line 1	−44.50% (−36.94)	−18.98% (−3803.09)	5.19% (1592.55)	0.00% (0.00)	−17.74% (−2.82)
	SH-Line 2	−40.11% (−35.29)	−34.07% (−10220.53)	4.29% (1616.63)	0.00% (0.00)	−33.08% (−7.86)
	SH-Line 3	−56.07% (−27.48)	−31.87% (−3348.62)	5.14% (664.59)	0.00% (0.00)	−30.83% (−2.57)
	SH-Line 5	−65.84% (−32.92)	−44.70% (−3071.10)	31.34% (1567.34)	0.00% (0.00)	−44.07% (−2.40)
	SH-Line 6	−69.64% (−43.87)	−17.43% (−1297.95)	0.00% (0.00)	30.46% (22440.93)	−16.17% (−0.95)
	SH-Line 7	−62.17% (−49.11)	−29.80% (−4531.66)	0.93% (190.95)	0.00% (0.00)	−28.72% (−3.46)
	SH-Line 8	−55.80% (−47.99)	−12.18% (−1843.22)	0.00% (0.00)	0.00% (0.00)	−10.84% (−1.30)
	SH-Line 9	−51.77% (−53.84)	−7.96% (−1611.06)	34.10% (9404.77)	0.00% (0.00)	−6.58% (−1.06)
	SH-Line 10	−42.56% (−23.41)	−24.64% (−3725.59)	0.00% (0.00)	15.99% (26597.23)	−23.49% (−2.81)
	SH-Line 11	−39.92% (−32.73)	−11.60% (−2392.19)	60.66% (13652.48)	0.00% (0.00)	−10.28% (−1.68)
	SH-Line 12	−63.97% (−46.70)	−39.64% (−6021.89)	0.00% (0.00)	32.01% (36809.27)	−38.72% (−4.66)
	SH-Line 13	−59.88% (−37.12)	−47.96% (−7897.27)	0.00% (0.00)	21.57% (24977.69)	−47.17% (−6.15)
	SH-Line 16	−55.89% (−34.09)	−16.46% (−1616.47)	170.52% (9836.12)	0.00% (0.00)	−15.30% (−1.19)
	SH-Line 17	−34.49% (−9.66)	−39.26% (−2822.11)	68.25% (3136.13)	0.00% (0.00)	−38.53% (−2.19)
Guangzhou	GZ-Line 4	−55.07% (−31.39)	−41.67% (−5447.91)	23.78% (2768.70)	0.00% (0.00)	−41.77% (−4.39)
	GZ-Line 5	−27.88% (−17.28)	−27.67% (−5869.81)	0.00% (0.00)	0.00% (0.00)	−27.67% (−4.72)
	GZ-Line 6	−40.13% (−22.07)	−26.80% (−4378.77)	0.00% (0.00)	30.83% (47904.33)	−26.80% (−3.52)
	GZ-Line 7	−26.64% (−6.13)	−35.21% (−2014.83)	0.00% (0.00)	9.73% (4676.85)	−35.47% (−1.63)
	GZ-Line 8	−26.27% (−10.25)	0.00% (−0.00)	0.00% (0.00)	61.87% (61432.57)	−0.08% (−0.01)
	GZ-Line 9	0.00% (−0.00)	−24.78% (−1471.49)	157.10% (4923.21)	123.30% (36153.98)	−24.84% (−1.19)
	GZ-Line 13	0.00% (−0.00)	−36.27% (−2710.67)	144.62% (5111.42)	46.95% (22703.99)	−36.34% (−2.18)
	GZ-Line 14	−35.21% (−11.27)	−51.25% (−7174.10)	121.65% (7087.50)	0.00% (0.00)	−51.25% (−5.77)
	GZ-Line 21	−37.15% (−11.14)	−57.82% (−8272.38)	75.70% (4869.10)	0.00% (0.00)	−57.82% (−6.65)

Table 4. *Cont.*

City	Line Name	Train	Energy (10^4 kwh)	Passenger Transport Volume (10^4 PT)	Revenue Passenger Kilometers (10^4 PK)	CO_2 (10^4 tons)
GZ-Guangfo Line		−39.83% (−15.14)	−21.55% (−2120.81)	0.00% (0.00)	4.42% (5293.87)	−21.55% (−1.71)
Shenzhen	SZ-Line 1	−52.26% (−44.42)	−30.13% (−6193.01)	0.00% (0.00)	0.00% (0.00)	−30.13% (−4.98)
	SZ-Line 2	−68.87% (−52.34)	−49.92% (−8033.73)	0.00% (0.00)	33.50% (32952.38)	−49.92% (−6.46)
	SZ-Line 3	−50.58% (−37.94)	−20.18% (−3226.14)	9.10% (2079.68)	0.00% (0.00)	−20.24% (−2.60)
	SZ-Line 4	−50.38% (−24.18)	−16.15% (−1564.35)	0.00% (0.00)	6.23% (7771.33)	−16.15% (−1.26)
	SZ-Line 5	−30.23% (−17.53)	−27.48% (−5734.49)	1.75% (513.67)	0.00% (0.00)	−27.48% (−4.61)
	SZ-Line 6	−53.24% (−14.91)	−28.05% (−1407.52)	74.48% (2708.38)	0.00% (0.00)	−28.05% (−1.13)
	SZ-Line 7	−41.95% (−17.20)	−44.05% (−6390.59)	0.00% (0.00)	80.58% (59081.94)	−44.05% (−5.14)
	SZ-Line 9	−54.02% (−25.93)	−60.52% (−11326.23)	0.00% (0.00)	49.71% (39498.59)	−60.52% (−9.11)
	SZ-Line 10	−39.21% (−10.20)	0.00% (−0.00)	120.56% (4742.59)	143.44% (41412.43)	0.00% (−0.00)

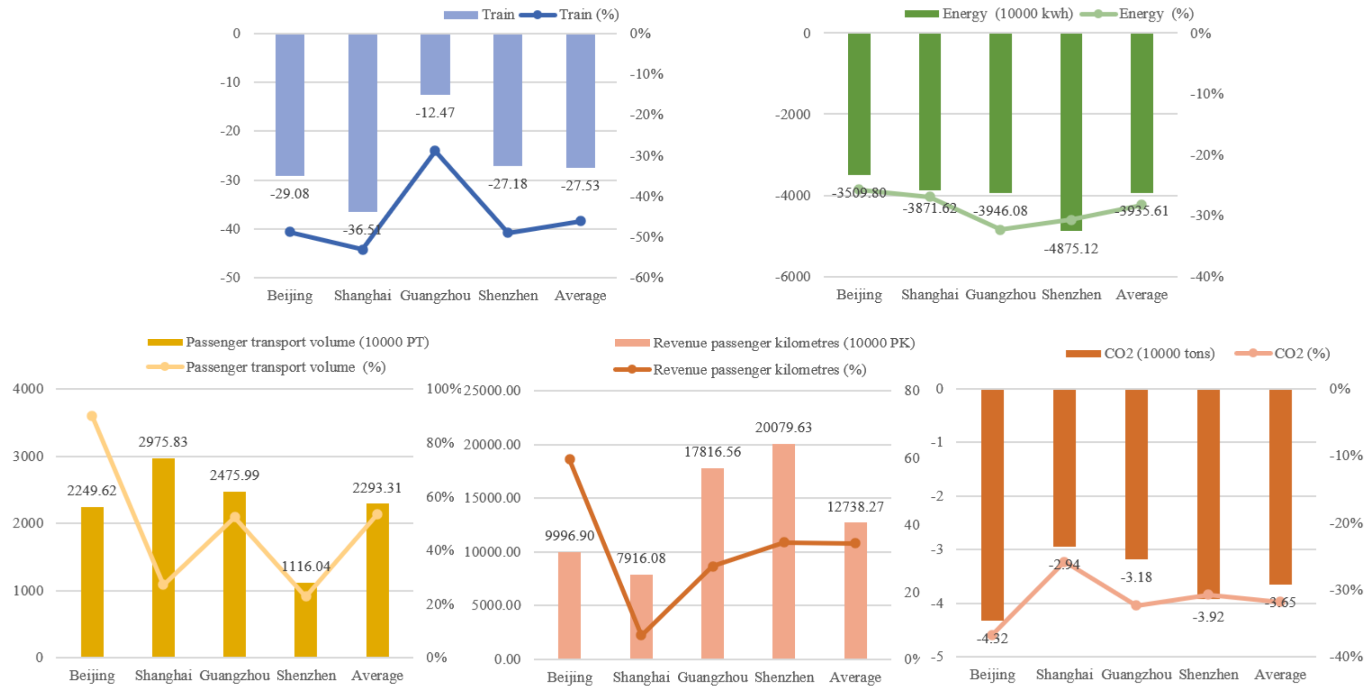

Figure 4. The average improvement values of the URT systems in case cities.

3.3.1. Input Adjustment Plan

In terms of the number of allocated trains, the average improvement value of 51 inefficient lines is 46.07% (27.53). Only three URT lines (i.e., BJ-Line S1, GZ-Line 9, and GZ-Line 13) reach the optimal level. In total, 20 URT lines are under the average level, while 28 lines are above the average level. From the perspective of operation, there is a need to calculate the optimal number of trains and develop a dynamic scheduling mechanism. Different types of trains (e.g., short trains can be used during the off-peak period) should be used to optimize overall efficiency. For instance, for SZ-Line 10, 39.21% (10.20) of trains can be reduced based on optimal efficiency. Furthermore, some lines, such as BJ-Line 8 (80.87%) and SH-Line 6 (69.64%), show a high improvement potential to reach the maximized resource utilization level. In this sense, attention should be paid to such URT lines to optimize the number of allocated trains. At the city level, the average improvement values of the number of allocated trains for Beijing, Shanghai, Guangzhou, and Shenzhen are −48.79%, −53.04%, −28.82%, and −46.07%, respectively. Namely, Shanghai tops the list, while Guangzhou is closer to the ideal level compared with other case cities.

Regarding energy, the average improvement value of the lines is 28.22% (39.35 million kWh). Only four URT lines (i.e., BJ-Line 16, BJ-Yanfang Line, GZ-Line 8, and SZ-Line 10) reach the optimal level. In total, 24 lines are under the average level, while 23 lines are above the average level. That is to say, for most of the URT lines, there is a lot of room to improve overall efficiency by reducing energy. For instance, based on the benchmark, the energy consumed by BJ-Line 6 can be reduced by around 43.31% (11.26 million kWh) to minimize energy wastage. Particularly, some lines (e.g., BJ-Line 7, BJ-Line 8, SH-Line 5, GZ-Line 14, GZ-Line 21, and SZ-Line 9) should take measures to improve the utilization of energy for their greater potential. At the city level, the average improvement values of the energy of Guangzhou (−32.30%) and Shenzhen (−30.72%) are larger than the average level, while those of Beijing (−25.73%) and Shanghai (−26.90%) are smaller than the average level. This indicates that the inefficient URT lines in Guangzhou and Shenzhen deserve more attention in terms of energy conservation.

3.3.2. Output Adjustment Plan

In addition to the input plan, an improvement plan to maximize outputs is demonstrated. Firstly, in terms of passenger transport volume, the average improvement value of the passenger transport volume of observed lines is 53.50% (22.93 million person-times). In total, 21 URT lines (e.g., BJ-Line 1, SH-Line 6, GZ-Line 5, and SZ-Line 1) reach the optimal level. However, 16 lines are under the average level, while 14 lines are above the average level. Some lines (e.g., BJ-Yanfang Line, Daxing Airport Express, and SH-Line 16,) should improve passenger transport volume as much as possible for the lower output. At the city level, the average improvement value of the passenger transport volume of Shenzhen's URT lines is the closest to the optimal level among the case cities (i.e., 22.88%). By contrast, based on the results, the improvement values of Beijing (i.e., 89.96%) and Guangzhou (i.e., 52.28%) are lower than the average level. The lines with great improvement potential should be encouraged to expand passenger transport volume.

As for revenue passenger kilometers, the average improvement value of the URT lines is 34.54% (127.38 million passenger kilometers). In total, 29 URT lines (e.g., BJ-Line 1 and SZ-Line 1) are optimized, while 3 lines are above the average level and 19 lines are lower than the average value. It can be seen that most of the URT lines have produced sufficient passenger turnover output, while some lines have great improvement potential in passenger turnover, such as BJ-Line 16 (i.e., 259.66%) and BJ-Yanfang Line (i.e., 520.04%). From the city perspective, the average improvement value of URT lines in Shanghai is 7.15%, which is closer to the optimal level. At another extreme, the average improvement value of the URT lines in Beijing is 59.49%, which is much lower than the optimal level. The situations for Guangzhou and Shenzhen are between them.

Concerning CO_2 emissions, the average improvement value of URT lines is 31.82% (36.5 kilotons). Only SZ-Line 10 reached the optimal level, while another 25 lines are above the average value and 26 are less than the average value. In particular, some lines are significantly lower than the optimal level, such as BJ-Line 7 (69.08%) and SZ-Line 9 (60.52%). There is a lot of room for these lines to decline CO_2 emissions to maximize environmental sustainability. At the city level, compared with other cities, the average improvement value of CO_2 emissions for the URT lines in Shanghai (25.82%) is closer to the ideal level. On the contrary, the largest gap between the actual CO_2 emissions and the ideal emissions can be found in Beijing's URT lines (36.74%).

4. Discussion

First, the improvement values reveal that the efficiency of the URT systems can be improved by reducing unessential wastage on the input side. In this sense, the number of the same type of trains can be appropriately reduced, and redundant trains can be sent to other lines or other cities to improve utilization. In terms of energy, for one thing, the application of new energy-saving technologies and the dynamic marshaling of trains according to real-time passenger flow can reduce the energy consumption of train traction. For another, new technology in heating and air conditioning equipment can be used to reduce the operation energy consumption of station facilities for heating and cooling. Reducing energy consumption reduces the corresponding undesirable carbon emissions, which is conducive to improving efficiency. In this sense, the infrastructure and facilities can be updated by adopting new technologies or management techniques. In response to this, for the URT lines built in the early period (e.g., BJ-Line 1 and SH-Line 2), the local authorities should encourage operators to upgrade the trains and station facilities by adopting new technologies to improve energy efficiency and reduce carbon emissions. Therefore, in addition, there is also a need for operators to collaborate with other stakeholders (e.g., the local government and research institutions) to develop a multi-dimensional method to improve passenger turnover efficiency for stations in different locations (e.g., a preference policy can be developed for those using other means of transportation during rush hours). Moreover, the efficiency of the URT systems can be enhanced by increasing desirable outputs. Based on the results, it can be seen that the operational efficiency of new lines is relatively lower than those built in the earlier period. Taking Shanghai as an example, the average operational efficiency of SH-Line 1 and SH-Line 2 is higher than that of SH-Line 16 and SH-Line 17. One reason might be that operational efficiency is associated with passenger volume. The operational efficiency of lines close to the city center is relatively high compared with the operational efficiency of those close to suburban areas. This provides a management implication, in that increasing passenger volume can help improve operational efficiency. On the one hand, the government should encourage URT operators to strengthen cooperation with other transportation service providers (e.g., bus companies, taxi companies, bike-sharing companies) and promote their joint operation to provide convenient transfer conditions to attract passenger flow. On the other hand, operators can develop a preference policy and adjust ticket prices, such as discount sales for inefficient lines at certain fixed times, in order to entice citizens to take rail transit. This may be an effective way to improve operational efficiency in the short term.

In addition, more investment should be made in advanced technologies, such as 5G communication technology, big data, artificial intelligence, and industrial Internet, to build smart URT systems to enhance efficiency. In terms of stations, existing stations can be upgraded to smart stations, which can provide passengers with intelligent security checks, intelligent customer service centers, intelligent guidance, and other services. A series of intelligent systems, such as intelligent passenger guide screens, multimedia platform screens, intelligent ticket machines, and intelligent customer service centers, can be installed to provide passengers with refined and intelligent travel services through the real-time perception, acquisition, and transmission of operation information. In terms of lines, on the one hand, new intelligent technologies should be applied to the operation and maintenance of lines to reduce relevant costs. On the other hand, new lines should be fully automated, which can save labor costs and improve efficiency. From this angle, the construction of smart URT systems is an important way to improve operational efficiency and energy efficiency and achieve better development in the URT sector.

5. Conclusions

With the unprecedented development of the URT in China, a certain number of studies have explored the evaluation of URT efficiencies. However, carbon emissions are rarely taken into account in the estimation process in existing studies. Considering the importance of emission reduction and URT line heterogeneity, this paper considers CO_2 as undesirable output and constructs an efficiency evaluation model based on the SBM, which can estimate the operational efficiency and energy efficiency for URT lines.

The proposed model was applied to evaluate the efficiency of 61 URT lines in four megacities in China. The empirical findings show that the URT lines in Guangzhou perform better in terms of operational efficiency, while the average energy efficiency of URT systems in Shanghai is higher than in other case cities. In addition, the average overall operational efficiency of URT lines in case cities is relatively low compared with energy efficiency, and there is a lot of room for improvement. A comparison of the efficiency of URT systems operated by state-owned enterprises and joint ventures indicates that state-owned enterprises are better at improving operational efficiency, while joint ventures are better at improving energy efficiency.

The limitations of this current paper should also be clarified, and some further research can be extended in the future. First, we only adopted the 2020 data of 61 URT lines in China to evaluate operational efficiency and energy efficiency in this paper. A study with more URT lines and multi-year panel data may explore the long-term dynamic changes in efficiency and obtain new management implications. Second, this paper does not consider service quality indicators from the passenger's perspective. URT systems aim to provide comfortable, convenient, and fast transport services for citizens. In future research, service quality factors such as transport congestion and service satisfaction degree can be adopted as outputs to comprehensively evaluate performance. Third, energy efficiency at the station level may provide a new perspective on energy saving and emission reduction for URT operations. In other words, more investigations can be conducted to provide deeper insights regarding energy efficiency at the station level. Last but not least, the convenience of transfer and joint operations between URT and bus systems may be important ways to improve operational efficiency and energy efficiency, which are also two important research directions that need to be further investigated.

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Appendix A

Based on the proposed model, the indicator of energy improvement potential can be defined as the ratio of the difference between the actual value and the target value to the actual value, i.e.:

$$PE_i = \frac{TE_i - XE_i}{XE_i} \tag{A1}$$

Generally speaking, the infrastructures of the URT system are difficult to adjust further in the short term once they have been constructed. Therefore, we aim to investigate the improvement potentials for train, energy, passenger transport volume, revenue passenger kilometers, and CO_2 emissions. Similarly, the targets of train, passenger transport volume, revenue passenger kilometers, and CO_2 emissions are expressed as follows:

$$TT_i = \sum_{j=1}^{n} \lambda_j XT_j \tag{A2}$$

$$TP_i = \sum_{j=1}^{n} \lambda_j YP_j \tag{A3}$$

$$TR_i = \sum_{j=1}^{n} \lambda_j YR_j \tag{A4}$$

$$TC_i = \sum_{j=1}^{n} \lambda_j YC_j \tag{A5}$$

Likewise, the improvement potentials of train, passenger transport volume, revenue passenger kilometers, and CO_2 emissions can be formulated as follows:

$$PT_i = \frac{TT_i - XT_i}{XT_i} \tag{A6}$$

$$PP_i = \frac{TP_i - YP_i}{YP_i} \tag{A7}$$

$$PR_i = \frac{TR_i - YR_i}{YR_i} \tag{A8}$$

$$PC_i = \frac{TC_i - YC_i}{YC_i} \tag{A9}$$

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