Coordination of public-private transport and sustainability measurement: A futuristic perspective in transport

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Abstract

Coordination in providing sustainable and effective transport services can be beneficial for both the public and private sectors. Although there is considerable research in each of public and private transport, the literature shows that research on public-private coordination is rare. Furthermore, performance measurement of public-private transport has been another less explored topic in transport systems. Based on these knowledge gaps, we make contributions to the transportation field by performance measurement and coordination of public-private transport within multimodal transport networks. In this paper, we model public-private transport networks by developing a novel network data envelopment analysis (NDEA) with some distinctive features. The model is built based on the directional distance function (DDF) and provides detailed insights into the sustainability and

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coordination of public-private transport networks operating in a supply chain. It also provides resource allocation among decision making units (DMUs).

Keywords: Data envelopment analysis (DEA); Public-private transport; Coordination; Performance measurement; Resource allocation.

1. Introduction

As transport plays a key role in strategic issues such as the economy, climate change, and healthcare, it has been considered a significant research direction in many areas. Transporting passengers in many megacities such as Tokyo, Hong Kong, Seoul, and London is typically based on public transport vehicles, including the metro and bus. These modes of transport are usually run either by the public sector or the private sector. Owing to the recent advances in digital technologies and analytical approaches, the coordination of public and private transport now is receiving considerable attention from decision-makers in transportation systems. This pushes public and private transport to improve performance by changing transport planning. This, in turn, requires novel methods for coordinating demands and available resources in public and private transport, simultaneously.

Sustainable transport has a considerable impact on societies and addresses ecological, social, and economic dimensions of transport. Based on formal statistics, roughly 25 percent of the produced CO2 in the world is stemmed from the transport sector (Zhao et al., 2020). A large proportion of green gas emissions in transport is due to consuming fossil fuels, which results in climate change (Boussauw and Vanoutrive, 2017). In addition, with the increasing population particularly in developing countries such as India and Indonesia, issues associated with transport are expected to be even much more complicated (Zope et al., 2019). As such, sustainable transport needs more attention in the transport sector by considering ecological, social, and economic dimensions. In this regard, sustainable transport aims to minimize ecological problems and maximize social and economic benefits for society (Stephenson et al., 2018). To do so, the focus of policymakers and managers of transport has been on adopting appropriate government policies, applying technology-based infrastructures, and collaborating with the public and private sectors (Soto et al., 2021).

In sustainable transport, the public and private sectors attempt to cooperate for achieving sustainability goals such as reduced costs, less pollution, and more satisfaction. To do so, optimal resource allocation and the right targets play significant roles. In this sense, allocation of the limited resources to the unlimited demands based on sustainability criteria in transport should be in a way that the most desirable outcome is obtained. Optimizing sustainable resource allocation in transport not only can prevent wasting resources but also increases the utility of passengers. Targets create directions for helping organizations to achieve objectives in line with their mission (Azadi et al., 2014). By setting clear-cut and achievable targets, organizations can better conduct their settings and get more insights into their activities. Furthermore, setting such targets can assist organizations in improving performance.

To achieve sustainable urban mobility objectives, public transport service providers develop performance measurement frameworks and systems based on passengers' expectations (Georgiadis et al., 2020). Nonetheless, public transport performance depends on different factors such as demographic characteristics, transport system features, services planning, resource allocation, and network design (de Grange et al., 2013). In multimodal public transport networks, the incorporation of information flow, inter alia, and network planning play key roles (Roukouni et al., 2012; Rybnicek et al., 2020). From a performance perspective, a lack of appropriate coordination among public transport sub-systems can affect the overall sustainability of the system significantly.

Having said that, the question is how we can develop a new network data envelopment analysis (NDEA) model to increase the coordination and performance of public-private transport systems. Another research question is how we can allocate a budget for public transportation systems. Moreover, how we can model different types of data in network structures using data envelopment analysis (DEA) technique. The main objective of this paper is to investigate the coordination and performance of public-private transport systems. These systems deal with multimodal public transport networks consisting of road and rail sub-systems. We model public-private transport systems in a megacity using a novel NDEA for measuring the performance and investigating coordination within these systems. Our developed model also is applied to sustainable resource allocation in public-private transport systems. The proposed model in this study is built using the directional distance function (DDF) in the NDEA structure. Moreover, since there are different types of data, including integer data, negative data, and undesirable outputs in our case study, we address these types of data to get more reliable results and provide more realistic insights to managers and decision-makers of transport systems. The main contributions of this study are as follows:

- A DDF is developed for measuring the overall and stage sustainability.
- The proposed NDEA model is formulated in the presence of integer data.
- The proposed NDEA model can deal with undesirable outputs.
- The proposed NDEA model can handle negative data.
- A resource allocation approach using the NDEA model is developed.

The rest of this paper is organized as follows: The related works are discussed in Section 2. The proposed method is given in Section 3. In Section 4, we provide a case study. Conclusions and research directions are presented in Section 5.

2. Literature review

The term "collaboration" is used for establishing a close, deep, and long-run relationship among organizations for solving joint problems (Wankmüller and Reiner, 2020). The collaboration between the public sector and private sector provides organizations with improved efficiency and reduced risk (Iossa and Martimort, 2015). The concept of public-private collaboration was initially proposed in the transport sector (Delmon, 2011; Grimsey and Lewis, 2004). Public-private collaboration now is observed in many strategic areas such as healthcare and education (Spoann et al., 2019). Several factors such as service quality, reduced time, and costs are applied to assess public-private transport collaborations (Rybnicek et al., 2020).

Sustainability is of substantial importance in transport as it provides society with numerous benefits in all economic, ecological, and social dimensions (Wanke et al., 2020). Sustainable transport as a sustainable and effective strategy addresses today's key challenges, including air pollution, climate change, and road accidents that adversely affect human life and health even for future generations (Stefaniec et al., 2021). In sustainable transport, the focus of the economic dimension is on the cost reduction of carrying goods and individuals. The environmental dimension mostly concentrates on factors such as fuel consumption and CO_2 emissions contributing to noise and air pollution and climate change. The social dimension also deals with individual quality of life and well-being in society (Shi et al., 2019). A sustainable transport system needs to meet several criteria (Gilbert et al., 2003). Firstly, it should be able to minimize energy consumption, noise pollution, carbon gas emissions, and the use of land. Secondly, individuals' needs for transportation to be met safely and efficiently. Thirdly, it should be able to provide individuals with different modes of transportation, be affordable, and support a dynamic economy. Performance evaluation and analysis of transportation systems considering sustainability criteria have received substantial attention over the last decade. Zito and Salvo (2011) presented some sustainable transport performance indicators for assessing the impacts of policy measures on urban transport. They integrated the indicators through equal weighting along with the Euclidean distance between cities based on the normalized transport sustainability index. Zhao et al. (2011) presented an assessment method named the downtown space reservation system for travel demand management strategy. To do so, they considered radial and slacks-based NDEA models in network structures. Haghshenas and Vaziri (2012) evaluated several cities considering the urban sustainable transport composite index. To do so, they selected sustainable transport metrics that encompass economic, environmental, and social dimensions. To allocate resources to rail and automotive systems, Vasco Correa (2012) proposed a DEA model. The results show that resource allocation in rail transport could be better compared with the road transport. Shiau and Liu (2013) presented an indicator system to assess and monitor sustainable urban transport. First, they categorized several indicators into economic, environmental, and social dimensions. Then, they used fuzzy cognitive maps and the analytic hierarchy process for constructing the cause-effect relationships between main indicators and for assessing sustainable urban transport strategies. Azadi et al. (2014) evaluated public transport service providers and set some attainable and realistic targets for the service providers based on economic and ecological indicators using a two-stage NDEA. Mahdinia et al. (2018) evaluated transport sustainability in the US using an indicator-based algorithm. The algorithm combines composite indices in all sustainable transport aspects for performance evaluation. Mahmoudi et al. (2019) identified the assessment indicators to assess the sustainability of urban transportation networks and then proposed a Best-Worst approach for evaluating and prioritizing sustainability aspects and assessment indicators. They also identified potential strategies and appropriate policies for achieving sustainability goals in urban transportation. Ganji et al. (2023) developed a double-frontier cross-efficiency technique to evaluate Iranian airlines' performance. They incorporated prospect theory into the cross-efficiency technique. Ganji and Rassafi (2019) proposed a double-frontier Malmquist productivity index to assess Iranian road safety performance. Ganji et al. (2020) have also evaluated Iranian road safety using a novel cross-efficiency technique based on evidential reasoning approach and the ordered weighted averaging operator. Gupta et al. (2021) applied a DEA model to compute the performance of vehicles on a variety of routes of the transport networks. They also proposed a fuzzy model for getting preferred compromise transportation solutions aimed at sustainable development.

Resource allocation as a tool of strategic planning to achieve organizational objectives is a way of allocating limited resources among different units of an organization for producing goods and services (Yu and Chen, 2016). There is a rich literature on resource allocation in the transport sector with a focus on implementing policies and providing sustainable services. Melachrinoudis and Kozanidis (2002) proposed a method for allocating resources to improve highway safety. To do so, they used an integer model with linear multiple-choice constraints. Mishra and Khasnabis (2012) proposed an approach for resource allocation to implement safety improvement alternatives for urban transport over different time horizons. The approach maximizes the profit and decreases cost considering crashes of different severity categories, budget limits, and other constraints. Given several congested resources, Churchill and Lovell (2012) proposed a two-stage stochastic integer model to allocate resources for potential capacity outcomes in air transport. The model presented by Churchill and Lovell (2012) coordinates the air traffic system by addressing uncertainty. Yu and Chen (2016) presented an NDEA model for resource allocation in container shipping companies. They also considered shared inputs, desirable, and undesirable outputs in their proposed model for reallocating resources. Wang et al. (2017) examined the problem of dynamic resource allocation in intermodal freight transport considering network effects. To do so, they applied the Markov decision process model and developed some mathematical models such as the approximation model and booking control model. Wu et al. (2018) developed a target setting and resource allocation method to enhance the ecological efficiency of decision making units (DMUs) in regional highway transportation systems. They incorporated the common weight technique in their proposed model to reallocate discretionary inputs and set output targets for DMUs. Yan et al. (2019) used price signals for modifying resource allocation and developed a co-optimization model of resource allocation and fare rates of high-speed trains in rail transport. Zhao et al. (2022) developed an NDEA model to allocate CO_2 emissions in transport systems. To do so, they combined two approaches with NDEA.

DEA as a nonparametric and applied technique is used for performance measurement and resource allocation of a set of peer DMUs (Amirteimoori et al., 2020; Charnes et al., 1978). The classic DEA models measure the performance of DMUs without considering the data type. One of these types of data is integer-valued data. There are some data in the performance evaluation of DMUs that are only integer-valued such as the number of staff in a hospital or the number of machines in a factory. Lozano and Villa (2006) embedded the integer data in DEA by presenting multi-integer linear programming. Their model was improved by Kazemi Matin and Kuosmanen (2009). Over the last decade, some scholars addressed integer-valued data in the DEA context, including Kazemi Matin and Emrouznejad (2011), Azadi and Farzipoor Saen (2014), and Fathi Ajirlo et al. (2019). Moreover, the traditional DEA models consider only non-negative data in performance evaluation and ignore negative data. By considering negative inputs as outputs and negative outputs as inputs, Scheel (2001) tackled the issue of negative data in DEA. A DDF model was developed for addressing this type of data by Portela et al. (2004). Kazemi Matin and Azizi (2011) and Tavana et al. (2018; 2021) also proposed models to deal with negative data in DEA. Undesirable output is considered another type of data that affects the obtained results by using DEA. CO_2 emissions produced by factories or cars are an example of undesirable output in real-world problems. Färe et al. (1989) were the first scholars to address undesirable outputs in DEA. Seiford and Zhu (2002) proposed a DEA model to reduce undesirable outputs. The issue of undesirable outputs has also been addressed over the last decade by several scholars such as Kalantary and Farzipoor Saen (2019); Mirhedayatian et al. (2014); Rashidi et al. (2015); Samavati et al. (2020), and Kazemi Matin et al. (2022).

The literature shows that performance measurement and coordination of public-private transport that operate in a supply chain have less been explored to date. Furthermore, sustainable resource allocation among DMUs in such a supply chain is another significant issue in the literature that needs to be explored by scholars. Moreover, the type of data, including integer data, undesirable data, and ratio data have not been considered in NDEA models by DDFs. The study in question makes several noteworthy contributions that advance the field of sustainability measurement and analysis. One of the main achievements of the study is the development of a DDF, which is a powerful tool for assessing sustainability at both the overall and stage levels. This new framework is a significant improvement over existing methods, as it offers a more comprehensive and nuanced approach to evaluating sustainability across different stages of production or development. Another key finding of the study is the formulation of an NDEA model that can handle integer and negative data, as well as undesirable outputs. This is a critical development because many existing models are limited in their ability to account for these types of data, which can be common in sustainability research. By overcoming this limitation, the proposed NDEA model represents a significant step forward in the field of sustainability analysis. Furthermore, the study also introduces a resource allocation approach that utilizes the NDEA model. This approach has important implications for real-world sustainability applications, as it provides a practical tool for decision-makers to optimize resource allocation and management in a sustainable manner. Overall, the contributions of this study have the potential to significantly advance our understanding of sustainability and help us make more informed decisions about how to promote sustainable development and resource management. In the next section, we address these issues by modeling the public-private transport networks of a megacity.

3. Proposed models

The efficiency and sustainability are two key factors in designing and operating public-private transport systems. Efficiency refers to the ability of a system to perform a task with the least amount of resources. Sustainability, on the other hand, refers to the ability of a system to meet the needs of the present without compromising the ability of future generations to meet their own needs. In the context of public-private transport systems, efficiency and sustainability are interdependent. A transport system that is efficient in terms of resource utilization, travel time, and cost can contribute to sustainability by reducing energy consumption, emissions, and traffic congestion. For example, a well-designed public transit system that uses clean energy sources and provides seamless connectivity can be more efficient and sustainable than individual car use. Moreover, a sustainable transport system can contribute to efficiency by reducing the negative externalities associated with individual transport modes. These negative externalities include air and noise pollution, traffic congestion, and accidents. In contrast, a transport system that is unsustainable may be more expensive to operate, require more resources, and have negative impacts on the environment and social equity. Therefore, a balanced approach that considers both efficiency and sustainability is crucial for designing and operating public-private transport systems. This requires the integration of various modes of transportation, the use of advanced technologies, and the adoption of policies that incentivize sustainable transport behavior (Daimi and Rebai, 2022).

To measure efficiency (sustainability) and coordinate the public-private transport network, we model the multimodal transport network consisting of bus service providers and metro stations based on DDF in the NDEA context. Table 1 depicts the used notations in this paper.

Table 1. The notations

Notations	**Descriptions**
x_{ij}	*i*th input of the DMU$_j$
$x_{ij}^{(k)}$	*i*th external input of the DMU$_j$ in the *k*th division
y_{rj}	*r*th output of the DMU$_j$
$y_{rj}^{(k)}$	*r*th external output of the DMU$_j$ in the *k*th division
z_{dj}	*d*th intermediate product of the DMU$_j$
λ_j	Intensifier variable of the DMU$_j$
$\lambda_j^{(k)}$	Intensifier variable of the DMU$_j$ in the *k*th division
f_{io}	*i*th direction of the x_{io}
g_{ro}	*r*th direction of the y_{ro}
g_{ro}^{U}	*r*th direction of the y_{ro} (undesirable output)
g_{ro}^{D}	*r*th direction of the y_{ro} (desirable output)
$f_{io}^{(k)}$	*i*th direction of the x_{io} in the *k*th division
$g_{ro}^{(k)}$	*r*th direction of the y_{ro} in the *k*th division

For n DMUs with m inputs and s outputs, consider x_{ij} $(i = 1,\ldots,m)$ and y_{rj} $(r = 1,\ldots,s)$ represent the inputs and outputs ($j = 1,\ldots,n$), respectively. The input distance function fixes the outputs at the current level to find the smallest ratio of inputs that can generate the current level of outputs. However, the output distance function fixes the inputs at the current level to identify the largest expansion of outputs that can be generated at the current level of inputs. These approaches can only use two points as touchstones to measure the efficiency of the production function: one in the input direction and the other one in the output direction. A setback that these approaches may face is that the efficiency of DMUs outside the cone generated by the efficient frontier will be overestimated. There is no need to fix inputs or outputs for efficiency measurement. It is possible to select every dominant point on the production function as a touchstone for efficiency measurement by defining a DDF. To measure the sustainability of DMUs, Chambers et al. (1996, 1998) defined DDF on the production possibility set (PPS) T as $\eta(\mathbf{x},\mathbf{y},\mathbf{f},\mathbf{g}) = \max\{\eta \mid (\mathbf{x}-\eta\mathbf{f}, \mathbf{y}+\eta\mathbf{g}) \in T\}$, where **f** and **g** are predefined directions. The DDF that measures DMU_o (the DMU under evaluation) in the direction of (**-f**, **g**) under variable returns to scale in the presence of negative data is as below:

$$
\begin{aligned}
& \max \eta_o \\
& \text{s.t.} \\
& \sum_{j=1}^{n} \lambda_j x_{ij} \le x_{io} - \eta_o f_i, \quad i = 1,\dots,m, \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro} + \eta_o g_r, \quad r = 1,\dots,s, \\
& \sum_{j=1}^{n} \lambda_j = 1, \\
& \lambda_j \ge 0, \quad j = 1,\dots,n, \\
& \eta_o \text{ unrestricted in sign.}
\end{aligned} \tag{1}
$$

where $\boldsymbol{\lambda} = (\lambda_1,\dots,\lambda_n)$ is a non-negative vector in R^n. Model (1) measures the distance of DMU_o from the efficient frontier in the direction of $(-\mathbf{f},\mathbf{g})$. In the optimal scenario, an objective value $\eta_o^* = 0$ implies a sustainable DMU, whereas $\eta_o^* > 0$ implies an unsustainable DMU. Moreover, $(\sum_{j=1}^{n} \lambda_j^* x_{ij}, \sum_{j=1}^{n} \lambda_j^* y_{rj})$ denotes the DMU_o, which is a benchmark for unsustainable DMUs. Model (1) can identify sustainable and unsustainable DMUs; however, it cannot measure the extent of unsustainability as the upper bound of η_o is unknown. Portela et al. (2004) proposed a range directional measure in which the largest step that can be taken by a DMU is used in a way that η_o becomes equal to or smaller than one. Here, $1-\eta_o$ is defined as sustainability. In particular, a direction is defined as:

$$
\begin{aligned}
& f_{io} = x_{io} - \min_{j=1,\dots,n}\{x_{ij}\}, \quad i = 1,\dots,m, \\
& g_{ro} = \max_{j=1,\dots,n}\{y_{rj}\} - y_{ro}, \quad r = 1,\dots,s.
\end{aligned} \tag{2}
$$

Thus, sustainability $1-\eta_o$ varies from 0 to 1. To measure sustainability, outputs are assumed to be disposable; i.e., they can be readily discarded. Although this assumption is reasonable for desirable outputs, the disposal of undesirable outputs may be costly. Färe et al. (1989) assumed that outputs are weakly disposable and developed a model to measure the efficiency in the presence of undesirable outputs. Assuming weak disposability of outputs, for b (undesirable outputs) and $s-b$ (desirable outputs), the constraints are as follows:

$$\begin{aligned}&\sum_{j=1}^{n}\lambda_j y_{rj} = y_{ro}-\eta_o g_{ro}^{U}, \quad r=1,\ldots,b,\\&\sum_{j=1}^{n}\lambda_j y_{rj} \geq y_{ro}+\eta_o g_{ro}^{D}, \quad r=b+1,\ldots,s.\end{aligned}\tag{3}$$

where $\mathbf{g}=(g_r^U, g_r^D)$ is a direction vector. Assuming weak disposability of outputs, the sustainability of DMU_o can be obtained by incorporating constraints (3) into Model (1), which is as follows:

$$\begin{aligned}&\max \eta_o\\&\text{s.t.}\\&\sum_{j=1}^{n}\lambda_j x_{ij} \leq x_{io}-\eta_o f_{io}, \quad i=1,\ldots,m,\\&\sum_{j=1}^{n}\lambda_j y_{rj} = y_{ro}-\eta_o g_{ro}^{U}, \quad r=1,\ldots,b,\\&\sum_{j=1}^{n}\lambda_j y_{rj} \geq y_{ro}+\eta_o g_{ro}^{D}, \quad r=b+1,\ldots,s,\\&\sum_{j=1}^{n}\lambda_j = 1,\\&\lambda_j \geq 0, \quad j=1,\ldots,n,\\&\eta_o \text{ unrestricted in sign.}\end{aligned}\tag{4}$$

Conventional DEA models assume that the inputs and outputs can only take real values. In many real-world applications, however, some inputs and/or outputs are only integer-valued. Assume that the inputs can be divided into $I = I^I \cup I^{NI} = \{1,\ldots,m\}$, and outputs can be divided into $O = O^I \cup O^{NI} = \{b+1,\ldots,s\}$, where I^I and O^I are the integer values and I^{NI} and O^{NI} are real values, respectively. Assuming weak disposable outputs and the presence of integer inputs and outputs, the sustainability of DMU_o is measured as below:

$$
\begin{aligned}
&\max \eta_o \\
&\text{s.t.} \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \le \tilde{x}_{io}, \quad i \in I^I, \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \le x_{io} - \eta_o f_{io}, \quad i \in I^{NI}, \\
&\sum_{j=1}^{n} \lambda_j y_{rj} = y_{ro} - \eta_o g_{ro}^{U}, \quad r = 1,\ldots,b, \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \ge \tilde{y}_{ro}, \quad r \in O^I, \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro} + \eta_o g_{ro}^{D}, \quad r \in O^{NI}, \\
&x_{io} - \eta_o f_{io} = \tilde{x}_{io}, \quad i \in I^I, \\
&y_{ro} + \eta_o g_{ro}^{D} = \tilde{y}_{ro}, \quad r \in O^I, \\
&\tilde{x}_{io}, \tilde{y}_{ro} \in \mathrm{Z}_{+}, \quad i \in I^I, r \in O^I, \\
&\sum_{j=1}^{n} \lambda_j = 1, \\
&\lambda_j \ge 0, \quad j = 1,\ldots,n, \qquad\qquad (5) \\
&\eta_o \text{ unrestricted in sign.}
\end{aligned}
$$

Figure 1 depicts a general two-division network. The first division uses $m^{(1)}$ external inputs $x_{ij}^{(1)}$ ($i = 1,\ldots,m^{(1)}$) to produce $s^{(1)}$ external outputs $y_{rj}^{(1)}$ ($r = 1,\ldots,s^{(1)}$), which are sent out of the network. Also, division 1 produces h intermediate products z_{dj} ($d = 1,\ldots,h$), which are used by the second division. The second division uses $m - m^{(1)}$ external inputs $x_{ij}^{(2)}$ ($i = m^{(1)} + 1,\ldots,m$) and h intermediate products z_{dj} ($d = 1,\ldots,h$) to produce $s - s^{(1)}$ outputs $y_{rj}^{(2)}$ ($r = s^{(1)} + 1,\ldots,s$).

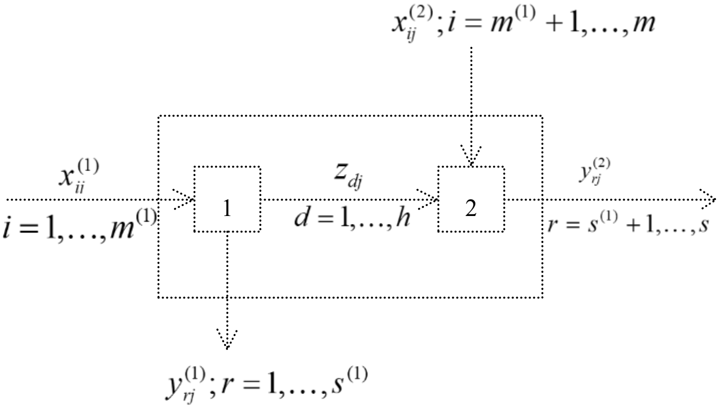

Figure 1. Structure of general two-division network

A variety of PPS has been defined in DEA literature for network systems. Färe and Grosskopf (2000) defined the PPS of a network system as an aggregate of PPSs of divisions. The PPS of the system shown in Figure 1 is defined as follows:

$$T^{\text{Network}} = \left\{ (\mathbf{x},\mathbf{y},\mathbf{z}) \left| \begin{array}{l} \sum_{j=1}^{n} \lambda_j^{(1)} x_{ij}^{(1)} \le x_i^{(1)}, i = 1,\ldots,m^{(1)}, \sum_{j=1}^{n} \lambda_j^{(1)} y_{rj}^{(1)} \ge y_r^{(1)}, r = 1,\ldots,s^{(1)}, \\ \sum_{j=1}^{n} \lambda_j^{(1)} z_{dj} \ge z_d, d = 1,\ldots,h, \sum_{j=1}^{n} \lambda_j^{(2)} x_{ij}^{(2)} \le x_i^{(2)}, i = m^{(1)}+1,\ldots,m, \\ \sum_{j=1}^{n} \lambda_j^{(2)} z_{dj} \le z_d, d = 1,\ldots,h, \sum_{j=1}^{n} \lambda_j^{(2)} y_{rj}^{(2)} \ge y_r^{(2)}, r = s^{(1)}+1,\ldots,s, \\ \sum_{j=1}^{n} \lambda_j^{(k)} = 1, k = 1,2, \lambda_j^{(k)} \ge 0, k = 1,2; j = 1,\ldots,n \end{array} \right. \right\} \tag{6}$$

The intermediate products z_d $(d = 1,\ldots,h)$ are produced and consumed within the system. For example, an intermediate product produced by Division 1 is expected to have maximum value so that Division 1 can be more sustainable. At the same time, it is expected to be as low as possible so that Division 2 can be more sustainable. Therefore, the supply and demand sides of intermediate products have contradictory objectives. Chen et al. (2016) used constraints $\sum_{j=1}^{n} \lambda_j^{(1)} z_{dj} = \hat{z}_d$ ($d = 1,\ldots,h$) and $\sum_{j=1}^{n} \lambda_j^{(2)} z_{dj} = \hat{z}_d$ $(d = 1,\ldots,h)$ to find the shared objective $\hat{z}_d$ for both divisions such that they would not be contradictory, where $\hat{z}_d$ ($d = 1,\ldots,h$) is a decision variable. This study uses the approach proposed by Chen et al. (2016). Thus, assuming variable returns to scale, to measure the sustainability of DMU_o, an NDEA model is proposed as follows:

$$
\begin{aligned}
\max \quad & \eta_o^S \\
\text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j^{(1)} x_{ij}^{(1)} \le x_{io}^{(1)} - \eta_o^S f_{io}^{(1)}, \quad i = 1,\ldots,m^{(1)}, \\
& \sum_{j=1}^{n} \lambda_j^{(2)} x_{ij}^{(2)} \le x_{io}^{(2)} - \eta_o^S f_{io}^{(2)}, \quad i = m^{(1)}+1,\ldots,m, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} z_{dj} = \hat{z}_{do}, \quad d = 1,\ldots,h, \\
& \sum_{j=1}^{n} \lambda_j^{(2)} z_{dj} = \hat{z}_{do}, \quad d = 1,\ldots,h, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} y_{rj}^{(1)} \ge y_{ro}^{(1)} + \eta_o^S g_{ro}^{(1)}, \quad r = 1,\ldots,s^{(1)}, \\
& \sum_{j=1}^{n} \lambda_j^{(2)} y_{rj}^{(2)} \ge y_{ro}^{(2)} + \eta_o^S g_{ro}^{(2)}, \quad r = s^{(1)}+1,\ldots,s, \\
& \sum_{j=1}^{n} \lambda_j^{(k)} = 1, \quad k = 1,2, \\
& \lambda_j^{(k)} \ge 0, \quad k = 1,2; j = 1,\ldots,n.
\end{aligned}
\tag{7}
$$

For Model (7), the direction is defined as below:

$$
\begin{cases}
f_{io}^{(1)} = x_{io}^{(1)} - \min\limits_{j=1,\ldots,n} \{x_{ij}^{(1)}\}, \quad i = 1,\ldots,m^{(1)}, \\
f_{io}^{(2)} = x_{io}^{(2)} - \min\limits_{j=1,\ldots,n} \{x_{ij}^{(2)}\}, \quad i = m^{(1)}+1,\ldots,m, \\
g_{ro}^{(1)} = \max\limits_{j=1,\ldots,n} \{y_{rj}^{(1)}\} - y_{ro}^{(1)}, \quad r = 1,\ldots,s^{(1)}, \\
g_{ro}^{(2)} = \max\limits_{j=1,\ldots,n} \{y_{rj}^{(2)}\} - y_{ro}^{(2)}, \quad r = s^{(1)}+1,\ldots,s.
\end{cases}
\tag{8}
$$

Then, sustainability $1-\eta_o^S$ varies from 0 to 1.

Theorem 1: Model (7) is always feasible.

Proof: Indeed,

$$
\begin{aligned}
& \lambda_o^{(k)} = 1, \quad \lambda_j^{(k)} = 0, \quad j = 1,\ldots,n; j \ne o; k = 1,2 \\
& \hat{z}_{do} = z_{do}, \quad d = 1,\ldots,h, \\
& \eta_o^S = 0,
\end{aligned}
$$

is a feasible solution to Model (7). □

The overall network sustainability can be obtained using Model (7). The sustainability of Division 1 is obtained as below:

$$\begin{aligned}
\max \quad & \eta_o^{(1)} \\
\text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j^{(1)} x_{ij}^{(1)} \le x_{io}^{(1)} - \eta_o^{(1)} f_{io}^{(1)}, \quad i = 1,\ldots,m^{(1)}, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} z_{dj} \ge z_{do}, \quad d = 1,\ldots,h, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} y_{rj}^{(1)} \ge y_{ro}^{(1)} + \eta_o^{(1)} g_{ro}^{(1)}, \quad r = 1,\ldots,s^{(1)}, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} = 1, \\
& \lambda_j^{(1)} \ge 0, \quad j = 1,\ldots,n.
\end{aligned} \tag{9}$$

Note that in Model (9), optimization is implemented on the indices of Division 1, and the remaining indices represent the interdependence between the two divisions. This enables the sustainability measurement of other divisions.

Theorem 2: Model (9) is always feasible.

Proof: Indeed,

$$\begin{aligned}
& \lambda_o^{(1)} = 1, \quad \lambda_j^{(1)} = 0, \quad j = 1,\ldots,n; j \ne o \\
& \eta_o^{(1)} = 0,
\end{aligned}$$

is a feasible solution to Model (9). $\square$

Finally, the sustainability of Division 2 is measured as:

$$
\begin{aligned}
\max \quad & \eta_o^{(2)} \\
\text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j^{(2)} x_{ij}^{(2)} \le x_{io}^{(2)} - \eta_o^{(2)} f_{io}^{(2)}, \quad i = m^{(1)}+1,\ldots,m, \\
& \sum_{j=1}^{n} \lambda_j^{(2)} z_{dj} \le z_{do}, \quad d = 1,\ldots,h, \\
& \sum_{j=1}^{n} \lambda_j^{(2)} y_{rj}^{(2)} \ge y_{ro}^{(2)} + \eta_o^{(2)} g_{ro}^{(2)}, \quad r = s^{(1)}+1,\ldots,s, \\
& \sum_{j=1}^{n} \lambda_j^{(2)} = 1, \\
& \lambda_j^{(2)} \ge 0, \quad j = 1,\ldots,n.
\end{aligned}
\tag{10}
$$

Theorem 3: Model (10) is always feasible.

Proof: The proof is similar to the proofs of Theorems 1 and 2. □

Assume that $I^{(k)} = I_1^{(k)} \cup I_2^{(k)}$ ($k = 1,2$), where $I_1^{(k)}$ ($k = 1,2$) is the set of the indices of integer-valued variables, while $I_2^{(k)}$ ($k = 1,2$) represents the indices of real-valued variables. Assume that $O^{(k)} = O_1^{(k)} \cup O_2^{(k)} \cup O_3^{(k)}$ ($k = 1,2$), where $O_1^{(k)}$ ($k = 1,2$) denotes the indices of integer-valued variables, $O_2^{(k)}$ ($k = 1,2$) is the set of indices of real-valued variables, and $O_3^{(k)}$ ($k = 1,2$) is the indices of undesirable outputs. Assume that $D = D_1 \cup D_2 = \{1,\ldots,h\}$, where D_1 is the indices of integer-valued variables, while D_2 denotes the indices of real-valued variables. The proposed NDEA model is as follows:

$$
\begin{aligned}
\max\quad & \eta_o^S \\
\text{s.t.}\quad & \sum_{j=1}^{n} \lambda_j^{(1)} x_{ij}^{(1)} \le \tilde{x}_{io}^{(1)}, \quad i \in I_1^{(1)}, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} x_{ij}^{(1)} \le x_{io}^{(1)} - \eta_o^S f_{io}^{(1)}, \quad i \in I_2^{(1)}, \\
& \sum_{j=1}^{n} \lambda_j^{(2)} x_{ij}^{(2)} \le \tilde{x}_{io}^{(2)}, \quad i \in I_1^{(2)}, \\
& \sum_{j=1}^{n} \lambda_j^{(2)} x_{ij}^{(2)} \le x_{io}^{(2)} - \eta_o^S f_{io}^{(2)}, \quad i \in I_2^{(2)}, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} z_{dj} = \hat{z}_{do}, \quad d \in D_1, \\
& \sum_{j=1}^{n} \lambda_j^{(2)} z_{dj} = \hat{z}_{do}, \quad d \in D_1, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} z_{dj} = \hat{z}_{do}, \quad d \in D_2, \\
& \sum_{j=1}^{n} \lambda_j^{(2)} z_{dj} = \hat{z}_{do}, \quad d \in D_2, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} y_{rj}^{(1)} \ge \tilde{y}_{ro}^{(1)}, \quad r \in O_1^{(1)}, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} y_{rj}^{(1)} \ge y_{ro}^{(1)} + \eta_o^S g_{ro}^{(1)}, \quad r \in O_2^{(1)}, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} y_{rj}^{(1)} = y_{ro}^{(1)} - \eta_o^S g_{ro}^{(1)}, \quad r \in O_3^{(1)}, \\
& \sum_{j=1}^{n} \lambda_j^{(2)} y_{rj}^{(2)} \ge \tilde{y}_{ro}^{(2)}, \quad r \in O_1^{(2)} \\
& \sum_{j=1}^{n} \lambda_j^{(2)} y_{rj}^{(2)} \ge y_{ro}^{(2)} + \eta_o^S g_{ro}^{(2)}, \quad r \in O_2^{(2)} \\
& \sum_{j=1}^{n} \lambda_j^{(k)} = 1, \quad k = 1,2, \\
& x_{io}^{(1)} - \eta_o^S f_{io}^{(1)} = \tilde{x}_{io}^{(1)}, \quad i \in I_1^{(1)}, \\
& x_{io}^{(2)} - \eta_o^S f_{io}^{(2)} = \tilde{x}_{io}^{(2)}, \quad i \in I_1^{(2)}, \\
& y_{ro}^{(1)} + \eta_o^S g_{ro}^{(1)} = \tilde{y}_{ro}^{(1)}, \quad r \in O_1^{(1)}, \\
& y_{ro}^{(2)} + \eta_o^S g_{ro}^{(2)} = \tilde{y}_{ro}^{(2)}, \quad r \in O_1^{(2)}, \\
& \hat{z}_{do} = \tilde{z}_{do}, \quad d \in D_1, \\
& \tilde{x}_{io}^{(1)}, \tilde{x}_{io}^{(2)}, \tilde{y}_{ro}^{(1)}, \tilde{y}_{ro}^{(2)}, \tilde{z}_{do} \in \mathrm{Z}_+, \quad i \in I_1^{(1)}, I_1^{(2)}, r \in O_1^{(1)}, O_1^{(2)}, d \in D_1, \\
& \lambda_j^{(k)} \ge 0, \quad k = 1,2; j = 1,\ldots,n.
\end{aligned}
\tag{11}
$$

where $(-\mathbf{f},\mathbf{g}) = (-\mathbf{f}^{(1)},-\mathbf{f}^{(2)},\mathbf{g}^{(1)},\mathbf{g}^{(2)})$ is a direction vector. A DMU is efficient if $\eta_o^{S*} = 0$. The inefficient DMUs have positive values of η_o^{S*}, and DMUs with less efficiency have larger values of

η_o^{S*}. The advantage of Model (11) is that different weights can be allocated to various inputs/outputs using different values of $(-\mathbf{f}^{(1)},-\mathbf{f}^{(2)},\mathbf{g}^{(1)},\mathbf{g}^{(2)})$. The following theorem can be stated about Model (11):

Theorem 4: Model (11) is always feasible.

Proof: The proof is similar to the proofs of Theorems 1 and 2. □

The sustainability of Division 1 is measured as follows:

$$
\begin{array}{ll}
\max & \eta_o^{(1)} \\
\text{s.t.} & \sum_{j=1}^{n} \lambda_j^{(1)} x_{ij}^{(1)} \le \tilde{x}_{io}^{(1)}, \quad i \in I_1^{(1)}, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} x_{ij}^{(1)} \le x_{io}^{(1)} - \eta_o^{(1)} f_{io}^{(1)}, \quad i \in I_2^{(1)}, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} z_{dj} \ge z_{do}, \quad d \in D_1, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} z_{dj} \ge z_{do}, \quad d \in D_2, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} y_{rj}^{(1)} \ge \tilde{y}_{ro}^{(1)}, \quad r \in O_1^{(1)}, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} y_{rj}^{(1)} \ge y_{ro}^{(1)} + \eta_o^{(1)} g_{ro}^{(1)}, \quad r \in O_2^{(1)}, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} y_{rj}^{(1)} = y_{ro}^{(1)} - \eta_o^{(1)} g_{ro}^{(1)}, \quad r \in O_3^{(1)}, \\
& \sum_{j=1}^{n} \lambda_j^{(1)} = 1, \\
& x_{io}^{(1)} - \eta_o^{(1)} f_{io}^{(1)} = \tilde{x}_{io}^{(1)}, \quad i \in I_1^{(1)}, \\
& y_{ro}^{(1)} + \eta_o^{(1)} g_{ro}^{(1)} = \tilde{y}_{ro}^{(1)}, \quad r \in O_1^{(1)}, \\
& \tilde{x}_{io}^{(1)}, \tilde{y}_{ro}^{(1)} \in Z_+, \quad i \in I_1^{(1)}, r \in O_1^{(1)}, \\
& \lambda_j^{(1)} \ge 0, \quad j = 1, \dots, n.
\end{array}
\qquad (12)
$$

where $(-\mathbf{f},\mathbf{g}) = (-\mathbf{f}^{(1)},-\mathbf{f}^{(2)},\mathbf{g}^{(1)},\mathbf{g}^{(2)})$ is a direction vector. Furthermore, a DMU is efficient if $\eta_o^{(1)*} = 0$; otherwise, it is inefficient. The constraints on the intermediate products in Model (12) are treated similarly to the constraints on the non-discretionary variables in the conventional DEA. No optimization is implemented on this set of constraints. The following theorem can be stated about Model (12):

Theorem 5: Model (12) is always feasible.

Proof: The proof is similar to the proofs of Theorems 1 and 2. □

The sustainability of Division 2 is obtained as follows:

$$
\begin{aligned}
\max \quad & \eta_o^{(2)} \\
\text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j^{(2)} x_{ij}^{(2)} \le \tilde{x}_{io}^{(2)}, \quad i \in I_1^{(2)}, \\
& \sum_{j=1}^{n} \lambda_j^{(2)} x_{ij}^{(2)} \le x_{io}^{(2)} - \eta_o^{(2)} f_{io}^{(2)}, \quad i \in I_2^{(2)}, \\
& \sum_{j=1}^{n} \lambda_j^{(2)} z_{dj} \le z_{do}, \quad d \in D_1, \\
& \sum_{j=1}^{n} \lambda_j^{(2)} z_{dj} \le z_{do}, \quad d \in D_2, \\
& \sum_{j=1}^{n} \lambda_j^{(2)} y_{rj}^{(2)} \ge \tilde{y}_{ro}^{(2)}, \quad r \in O_1^{(2)} \\
& \sum_{j=1}^{n} \lambda_j^{(2)} y_{rj}^{(2)} \ge y_{ro}^{(2)} + \eta_o^{(2)} g_{ro}^{(2)}, \quad r \in O_2^{(2)} \\
& \sum_{j=1}^{n} \lambda_j^{(2)} = 1, \\
& x_{io}^{(2)} - \eta_o^{(2)} f_{io}^{(2)} = \tilde{x}_{io}^{(2)}, \quad i \in I_1^{(2)}, \\
& y_{ro}^{(2)} + \eta_o^{(2)} g_{ro}^{(2)} = \tilde{y}_{ro}^{(2)}, \quad r \in O_1^{(2)}, \\
& \tilde{x}_{io}^{(2)}, \tilde{y}_{ro}^{(2)} \in \mathrm{Z}_+, \quad i \in I_1^{(2)}, r \in O_1^{(2)}, \\
& \lambda_j^{(2)} \ge 0, \quad j = 1, \ldots, n.
\end{aligned}
\tag{13}
$$

where $(-\mathbf{f}, \mathbf{g}) = (-\mathbf{f}^{(2)}, \mathbf{g}^{(2)})$ is a direction vector. Moreover, a DMU is efficient if $\eta_o^{(2)*} = 0$; otherwise, it is inefficient. The following theorem can be stated about Model (13):

Theorem 6: Model (13) is always feasible.

Proof: The proof is similar to the proofs of Theorems 1 and 2. □

3.1. A network DEA model for resource allocation

The fair allocation of resources and budget among a set of DMUs is very important for organizations (Amirteimoori et al., 2016). Cook and Zhu (2005) proposed an approach for resource allocation. However, their model cannot deal with DMUs with network structures. They assumed the budget as a non-discretionary input. To allocate budget *R* for *n* DMUs, resource allocation for Division 2 can be obtained by solving the following linear programming problem with an arbitrary objective function *P*, which is as follows:

$$\begin{aligned} &\min \quad P \\ &\text{s.t.} \sum_{j\in F} \lambda_j^{(2)t^*} r_j = r_t, \quad t \in N, \\ &\sum_{j=1}^{n} r_j = R \end{aligned} \tag{14}$$

where F denotes the set of sustainable DMUs and N represents the set of unsustainable DMUs in Model (13). In addition, $\lambda_j^{(2)t^*}$ denotes the optimal values in Model (13) when evaluating the unsustainable DMUs ($t \in N$). The same approach can be applied to Division 1.

4. Case study

Tehran is the capital of Iran. The population of Tehran is roughly 9 million in the city and more than 15 million in the larger metropolitan area of Great Tehran. Tehran is the most populous city in the country. The transport system of Tehran is so complicated due to overpopulation, geographical characteristics, and size. It provides transport services to 9 million residents as well as more than 1 million people who commute daily to Tehran from the suburbs. The road network of Tehran covers more than 3500 km for passenger transportation. Due to population, unprecedented growth, and increased economic activities, air pollution and heavy traffic are major challenges in this megacity. Sustainable transport development has been considered the most reliable and effective way to tackle these challenges. The strategies and plans for the future of Tehran transport are based on a sustainable development approach. In Tehran megacity, buses and metro are the most important modes of public transport. Bus services are mostly provided by the private sector while metro services are provided by the governmental sector. In this regard, measuring sustainability and coordination of public-private transport and resource allocation have been significant matters for managers and decision-makers of the transport system of Tehran.

Here, to investigate the sustainability and coordination of public-private transport as well as resource allocation based on sustainability indicators, we deal with a supply chain consisting of bus service providers (stage 1) and metro stations (stage 2). In stage 1, there are four inputs, including the number of seats, operating network, staff cost, and fuel cost. The outputs of stage 1 are CO2 emissions, profit, and number of arriving passengers. The number of passengers' complaints, the number of passengers, the average time spent on transferring, and the percentage of accurate data sharing are intermediate indicators between stage 1 and stage 2. In stage 2, the inputs include the number of passengers, maintenance cost, staff cost, and personnel training cost. The number of people traveled and profit are outputs of stage 2. Figure 2 shows the supply chain structure.

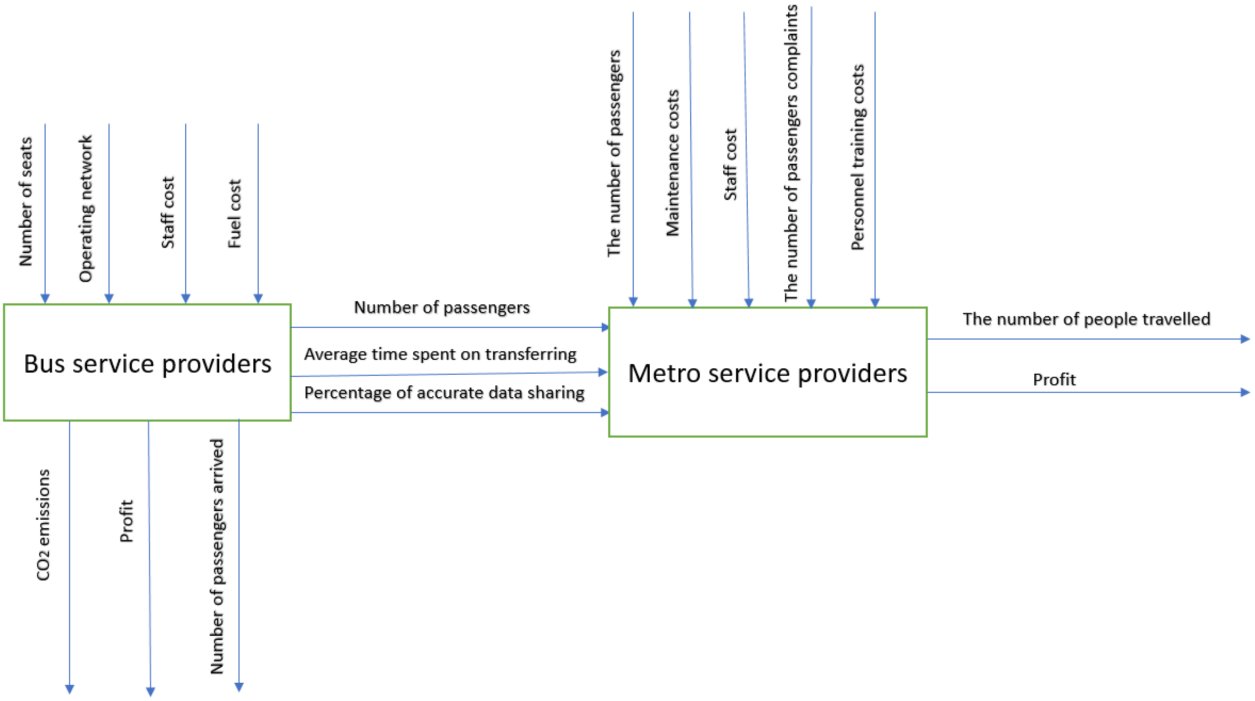

Fig. 2. The supply chain structure

Figure 2 provides an interesting structure for investigating the sustainability and coordination of public-private transport systems. The focus on a supply chain consisting of bus service providers and metro stations is particularly relevant given the increasing need for sustainable transport solutions in urban areas. One interesting aspect of Figure 2 is the inclusion of sustainability indicators as a basis for resource allocation. This highlights the importance of taking a holistic approach to transport system design and operation, which considers not only economic factors but also environmental and social factors. By integrating sustainability indicators into the structure, it becomes possible to evaluate the sustainability of different transport options and allocate resources accordingly. The use of intermediate indicators between stage 1 and stage 2 is also noteworthy. These indicators, such as the number of passengers' complaints, the average time spent on transferring, and the percentage of accurate data sharing, can provide valuable insights into the effectiveness of the transport system and identify areas for improvement. By tracking these indicators, it becomes possible to identify unsustainabilities and make adjustments to improve the overall sustainability of the system. Overall, Figure 2 emphasizes the importance of taking a holistic approach to transport system and operation and highlights the value of sustainability indicators in resource allocation and system evaluation.

Table 2 presents the variables used in this case study. Also, Table 3 reports the dataset, which dates back to 2021 and was gathered from archives and documents of bus service providers and Tehran Urban & Suburban Railway Company.

Table 2. The used variables

Stages	**Variables**	**Variable type**	**Variable nature**	**Notation**	**Sustainability dimension**	**Measurement unit**

Bus service providers (Stage 1)	Number of seats (Azadi et al., 2014)	Input	Integer	$x_1^{(1)}$	Economic	Number
	Operating network (Azadi et al., 2014)	Input	Real	$x_2^{(1)}$	Economic	Km
	Staff cost (Mirhedayatian et al., 2014)	Input	Real	$x_3^{(1)}$	Economic	Rial
	Fuel cost (Azadi et al., 2014)	Input	Real	$x_4^{(1)}$	Economic	Rial
	CO_2 emissions (Farzipoor Saen et al., 2022)	Output	Undesirable	$y_1^{(1)}$	Environmental	Kg
	Profit (Kazemi Matin et al., 2022)	Output	Real	$y_2^{(1)}$	Economic	Rial
	The number of passengers (Azadi et al., 2014)	Output	Integer	$y_3^{(1)}$	Economic	Number
	The number of passengers (Azadi et al., 2014)	Intermediate	Integer	z_1	Economic	Number
	Average time spent on transferring (Espino and Román, 2020)	Intermediate	Real	z_2	Economic	Second
	Percentage of accurate data sharing (Cottrill and Derrible, 2015)	Intermediate	Ratio	z_3	Economic	Percentage
Metro stations (Stage 2)	The number of passengers' complaints (Atalik, 2007)	Input	Integer	$x_1^{(2)}$	Economic	Number
	The number of passengers (Azadi et al., 2014)	Input	Integer	$x_2^{(2)}$	Economic	Number
	Maintenance costs (Azadi et al., 2014)	Input	Real	$x_3^{(2)}$	Economic	Rial
	Staff costs (Izadikhah et al., 2021)	Input	Real	$x_4^{(2)}$	Economic	Rial
	Personnel training costs (Izadikhah et al., 2021)	Input	Real	$x_5^{(2)}$	Social	Rial
	The number of people (Azadi et al., 2014)	Output	Integer	$y_1^{(2)}$	Economic	Number
	Profit (Kazemi Matin et al., 2022)	Output	Real	$y_2^{(2)}$	Economic	Rial

Table 3. The dataset

	Bus services providers (Stage 1)										Metro services providers (Stage 2)						
	Inputs				Outputs			Intermediates			Inputs					Outputs	
Supply chains (DMUs)	Number of seats (Integer)	Operating network (Km)	Staff cost (1000 Rial)	Fuel cost (10000 Rial)	CO_2 emission (10000 Kg) (Undesirable)	Profit (10000 Rial)	Number of passengers arrived (Integer)	Number of passengers (Integer)	Average time spent on transferring (Second)	Percentage of accurate data sharing (Ratio)	Number of passengers' complaints (Integer)	Number of passengers (Integer)	Maintenance costs (1,000 Rial)	Staff cost (1000,000) (Rial)	Personnel training costs (1000 Rial)	Number of people traveled (Integer)	Profit (1000 Rial)
1	5419	117	25141650	1977935	512	17565378	2969025	1785459	241	96	217	2547846	10593493	21644	315700	4337305	-15743000
2	7163	149	34854436	2413833	608	20837910	3617875	2607217	195	98	301	2862320	12835131	24121	391030	5469531	-11494920
3	3831	92	18393192	1983712	372	10399013	1734910	1068484	217	93	174	1973018	8193201	15729	213580	3041502	-7311539
4	5195	131	24975861	2115310	551	18972238	3191618	2291763	214	96	191	2102198	9948520	23938	371000	4393961	-9643641
5	4727	112	21836870	1601839	503	16937631	2518209	1681915	191	95	214	2297103	11938978	18349	282210	3979018	-12961390
6	6531	134	35118095	2393637	596	19175342	3325293	2064935	174	97	357	2753174	13965128	26865	412000	4818109	-15937928
7	3428	84	15846291	1593198	271	8997018	1417275	1248936	197	99	127	1428965	6753746	16106	184400	2677901	-9149793
8	5938	141	28753250	2338721	532	19396484	3294283	2193947	142	95	183	2302958	9853604	19328	445000	4496905	-17868951
9	3193	81	13826875	1427839	235	8136928	1992195	1529193	178	94	219	1085932	7492041	15484	201460	2615125	-10321927
10	4931	134	23291595	1824193	547	19382512	2916441	1413947	249	98	315	1912428	10124427	15138	217431	3326375	-8139418
11	7541	162	38109531	3937592	685	27541485	4532164	3364395	213	95	364	2533175	10197426	32421	450164	5897570	-9186563
12	3654	93	13928108	1695537	283	8583928	1638927	1134387	141	98	186	1043937	6028948	12937	219481	2178324	285753
13	5653	125	23644329	1853175	497	19472436	3232463	2243149	175	97	254	2321744	8643164	19875	273140	4564893	-11748340
14	4265	118	20648145	1843015	519	12541256	2174828	1378064	246	98	196	1842912	9255173	12820	201538	3220976	237124
15	6173	121	31932816	2048391	482	15847927	2927302	1737138	201	95	293	1865937	10436429	21194	375185	3603075	-8937928
16	3957	117	18674875	1798968	347	11073264	1953194	1246287	194	97	115	2285674	6786653	10187	145864	3527374	0
17	5751	135	26875956	2187377	548	18672932	3284283	2193982	228	95	253	2138289	8672623	19846	295970	4332271	-7765493
18	6847	142	33827329	2374839	523	17849018	3492190	2045744	234	94	307	1598739	11847384	21637	312743	3644483	-4675253
19	4593	96	19823018	1135307	412	12572073	2063153	1295482	197	97	252	1848327	7643932	16473	314931	3143809	-15732850
20	7749	155	37645173	2864836	645	22947541	3986.193	2584270	239	94	329	2194583	14842017	22947	315924	4778853	-14842927
21	3275	84	15865578	1697533	301	9137640	1586875	1478875	212	99	128	1783404	6475690	13972	157885	3262279	-3942881
22	5176	110	23926521	1732026	473	16937721	2434183	1257937	193	97	171	2018963	6836027	17936	192614	3276900	764,95

23	4141	97	19932182	1384163	416	15267542	2042395	1398641	185	99	149	2595173	9175031	19105	353972	3993814	-13523742
24	7382	159	35028191	2793145	632	19846741	3521938	2846173	209	96	282	3116186	9373928	21854	294119	5962359	19105
25	4519	115	21103938	1523910	487	15919101	2849519	2084913	213	97	178	2917029	8143219	19047	217163	5001942	196853
26	3794	108	17937642	1739015	352	11948721	2014943	1439294	173	99	194	2392830	7939204	14862	196264	3832124	-1964415
27	6937	141	36917617	2513178	617	21737527	3429936	2541191	185	95	312	3193548	13027539	24194	453932	5734739	-863043
28	5218	123	23917140	2018825	545	17927019	3196268	2018917	214	97	210	2719163	8961528	20917	261189	4738080	-9864421
29	5520	115	25085159	1796153	471	19017562	3392183	2429191	221	95	149	2819186	8018716	19528	301197	5248377	-10743963
30	3179	83	15983210	1694028	310	8942329	1429193	1284104	141	98	174	1837054	6917109	15935	132018	3121158	-5843311
31	7372	132	31294193	2018735	567	21654926	3736129	2472190	182	97	319	2582573	9385391	22917	321632	5054763	-8836102
32	4268	101	19018684	1302572	432	15183729	2321503	1494823	205	97	237	1943793	12834793	19762	329793	3438616	-13927945
33	6274	126	35591735	2193187	605	18928739	3422593	2321830	186	99	396	2941893	15938748	26937	496176	5263723	-16563732
34	5839	131	27836264	2286927	539	17057827	2749295	1937436	211	95	343	2193835	11926186	19031	294935	4131271	-16865095
35	3683	115	19836072	2191436	391	9846753	1583927	1138937	231	95	284	1638919	10937131	14648	247918	2777856	-9864742
36	6112	141	33383037	2124711	585	18938262	3186028	1938022	154	98	312	2582771	11549263	24194	398226	4520793	-12938658
37	4427	108	19083836	1393725	467	15654718	2381366	1382165	178	97	193	1856285	9745286	16438	214944	3238450	-5419452
38	4915	131	23837594	1864542	516	18745625	3093864	2194871	213	98	208	2492861	11083337	16936	312947	4687732	-7586315
39	3593	85	14864279	1586428	328	9643718	1386426	943745	196	96	159	1486439	5975427	12874	176973	3041502	-7311539
40	5837	122	26938910	2284718	541	16947632	3193836	1884736	251	98	193	2387592	11848374	22193	321945	4272328	-16948535
41	4382	98	19642783	1278842	473	14936665	2287524	1493826	218	97	237	2082837	9837252	16937	279176	3576663	-10847351
42	7365	161	36928761	2794673	645	21747453	3828365	2973634	201	97	294	2684563	10873623	25928	427393	5658197	-13876127
43	5137	125	24948759	2287371	539	18934726	3193746	1973327	217	95	231	2736252	7936262	18847	312920	4709579	-9374634
44	6245	142	36928632	2593836	601	20184746	3492842	2382947	193	98	329	2947272	15193845	25937	419273	5330219	-11865295
45	4538	107	20818387	1493922	458	15938232	2385479	1864292	175	97	212	2649473	7943627	16937	251984	4513765	17994
46	5072	113	24937363	1863537	499	17284635	2784829	2284639	209	98	237	2791634	9635284	20272	301833	5076273	-4856459
47	3329	87	15937308	1693643	317	9638365	1693735	967252	193	96	184	2193639	7826341	14991	196390	3160891	-1864284
48	5837	132	27465362	2257938	542	18837635	3402384	1938746	274	98	196	2602746	8937353	20187	293473	4541492	-8654301
49	5175	105	21939441	1784617	395	13958465	2392392	1973629	219	95	201	2492193	10793826	18764	301831	4465822	-11884914
50	3463	91	16793735	1783720	317	9534289	1580263	1194374	193	96	189	1975239	7177384	13936	189310	3169613	-5765462
51	7782	153	35018310	2691813	619	21937354	3918367	3193792	218	96	352	2692027	13937359	26452	427395	5885819	-9635289

4.1 Results and discussions

The results show the sustainability, coordination of public-private transport, and resource allocation based on sustainability indicators. In the first stage, there are bus service providers that are responsible for transporting people to different spots. In the second stage, metro stations play a key role in transporting people by public transport. Both stages in the supply chain of transport deal with all aspects of sustainability. Assuming variable returns to scale and using Model (11), we measure the sustainability of 51 supply chains of public-private transport. Table 4 depicts the results. As is seen, 35 out of 51 supply chains are sustainable. Supply chain 34 has the lowest sustainability score (0.7982). Also, this supply chain is unsustainable in stage 1 and stage 2 with sustainability scores of 0.8117 and 0.8991, respectively. In stage 1, the inputs' targets for supply chain 34 are 5793 (the number of seats), 120.9123 (operating network), 25009808.3246 (staff cost), and 2054582.6140 (fuel cost). The targets for intermediate variables, including the number of passengers, average time spent on transferring, and percentage of accurate data sharing are 2057658, 202.9012, and 96.6935, respectively.

Supply chain 34 also needs to improve output values in both stages. In stage 1, this supply chain should reduce CO_2 emissions to 509.5439. Also, profit and the number of arriving passengers should increase to 19172950.9825 and 2749341, respectively. Moreover, in stage 2, the number of people travelled should increase to 4131317 and profit should increase to 13404836.193. Columns 3 to 5 of Table 4 represent projection points of intermediate products. For sustainable supply chains, the projection point corresponding to the intermediate variables of supply chain 5 differs from its original data (intermediate products). This is acceptable as NDEA models do not directly optimize intermediate products. Columns 6-10 of Table 4 provide projection points for the integer inputs and outputs.

Table 4. The sustainability scores and projection points of DMUs using Model (11)

DMU_j	Overall sustainability $(1-\eta_j^{S*})$	$\hat{z}_{1j}$	$\hat{z}_{2j}$	$\hat{z}_{3j}$	$\tilde{x}_{1j}^{(1)}$	$\tilde{x}_{1j}^{(2)}$	$\tilde{x}_{2j}^{(2)}$	$\tilde{y}_{3j}^{(1)}$	$\tilde{y}_{1j}^{(2)}$
1	0.9216	2139473	215.5475	95.9702	5411	209	2547838	2969033	4337313
2	0.9624	2604926	195.1970	97.3366	7156	294	2862313	3617882	5469538
3	0.8983	1512967	184.9483	96.3868	3825	168	1973012	1734916	3041508
4	1.0000	2291763	214	96	5195	191	2102198	3191618	4393961
5	1.0000	1592700	227.0576	97.1108	4727	214	2297103	2518209	3979018
6	0.8884	2373878	194.8930	97.6058	6504	330	2753147	3325320	4818136
7	1.0000	1248936	197	99	3428	127	1428965	1417275	2677901
8	0.9559	2109643	211.6921	95.8792	5935	180	2302955	3294286	4496908
9	1.0000	1529193	178	94	3193	219	1085932	1992195	2615125
10	1.0000	1413947	249	98	4931	315	1912428	2916441	3326375
11	1.0000	3364395	213	95	7541	364	2533175	4532164	5897570
12	1.0000	1134387	141	98	3654	186	1043937	1638927	2178324
13	1.0000	2243149	175	97	5653	254	2321744	3232463	4564893
14	1.0000	1378064	246	98	4265	196	1842912	2174828	3220976
15	0.8483	2122680	208.8660	95.6099	6146	266	1865910	2927329	3603102
16	1.0000	1246287	194	97	3957	115	2285674	1953194	3527374
17	0.9058	2096328	204.4297	96.3566	5738	240	2138276	3284296	4332284
18	1.0000	2045744	234	94	6847	307	1598739	3492190	3644483
19	1.0000	1295482	197	97	4593	252	1848327	2063153	3143809
20	1.0000	2584270	239	94	7749	329	2194583	3986193	4778853
21	1.0000	1478875	212	99	3275	128	1783404	1586875	3262279
22	1.0000	1257937	193	97	5176	171	2018963	2434183	3276900
23	1.0000	1398641	185	99	4141	149	2595173	2042395	3993814
24	1.0000	2846173	209	96	7382	282	3116186	3521938	5962359
25	1.0000	2084913	213	97	4519	178	2917029	2849519	5001942
26	0.9747	1488838	187.7678	96.7158	3792	192	2392828	2014945	3832126
27	1.0000	2541191	185	95	6937	312	3193548	3429936	5734739
28	1.0000	2018917	214	97	5218	210	2719163	3196268	4738080
29	1.0000	2429191	221	95	5520	149	2819186	3392183	5248377
30	1.0000	1284104	141	98	3179	174	1837054	1429193	3121158
31	1.0000	2472190	182	97	7372	319	2582573	3736129	5054763
32	1.0000	1494823	205	97	4268	237	1943793	2321503	3438616
33	1.0000	2321830	186	99	6274	396	2941893	3422593	5263723

34	0.7982	2057658	202.9012	96.6935	5793	297	2193789	2749341	4131317
35	0.8817	1364416	169.9480	97.8576	3663	264	1638899	1583947	2777876
36	0.8985	2041782	208.0387	98.0631	6092	292	2582751	3186048	4520813
37	1.0000	1382165	178	97	4427	193	1856285	2381366	3238450
38	1.0000	2194871	213	98	4915	208	2492861	3093864	4687732
39	1.0000	943745	196	96	3593	159	1486439	1386426	3041502
40	0.9359	2134009	210.6691	96.8878	5832	188	2387587	3193841	4272333
41	1.0000	1493826	218	97	4382	237	2082837	2287524	3576663
42	1.0000	2973634	201	97	7365	294	2684563	3828365	5658197
43	1.0000	1973327	217	95	5137	231	2736252	3193746	4709579
44	0.8832	2358944	204.0391	96.8952	6220	304	2947247	3492867	5330244
45	1.0000	1864292	175	97	4538	212	2649473	2385479	4513765
46	1.0000	2284639	209	98	5072	237	2791634	2784829	5076273
47	1.0000	967252	193	96	3329	184	2193639	1693735	3160891
48	0.8889	2318299	214.2658	96.0621	5828	187	2602737	3402393	4541501
49	0.9535	2087923	203.4774	94.6887	5171	197	2492189	2392396	4465826
50	0.9595	1439417	186.2427	96.4444	3460	186	1975236	1580266	3169616
51	1.0000	3193792	218	96	7782	352	2692027	3918367	5885819

Table 5 represents the results obtained from Models (12)-(14). Column 2 reports the sustainability scores of the supply chains obtained from Model (12). According to Table 5, in stage 1, 42 out of 51 supply chains are sustainable. Supply chain 34 has the lowest sustainability score. Columns 3 and 4 of Table 5 list the projection points obtained from Model (12) for integer inputs and outputs.

Table 5. The results obtained from Models (12)-(14)

DMU_j	Stage 1			Stage 2				
	Sustainability $(1-\eta_j^{(1)*})$	$\widetilde{x}_{1j}^{(1)}$	$\widetilde{y}_{3j}^{(1)}$	Sustainability $(1-\eta_j^{(2)*})$	$\widetilde{x}_{1j}^{(2)}$	$\widetilde{x}_{2j}^{(2)}$	$\widetilde{y}_{1j}^{(2)}$	r_j
1	1.0000	5419	2969025	1.0000	217	2547846	4337305	170000000000
2	1.0000	7163	3617875	1.0000	301	2862320	5469531	137514422166
3	0.9540	3801	1863618	1.0000	174	1973018	3041502	0.0000
4	1.0000	5195	3191618	1.0000	191	2102198	4393961	0.0000
5	1.0000	4727	2518209	1.0000	214	2297103	3979018	0.0000
6	0.9338	6309	3405223	1.0000	357	2753174	4818109	0.0000
7	1.0000	3428	1417275	1.0000	127	1428965	2677901	0.0000
8	0.9308	5747	3379979	1.0000	183	2302958	4496905	0.0000
9	1.0000	3193	1992195	1.0000	219	1085932	2615125	0.0000
10	1.0000	4931	2916441	0.8750	290	1912403	3655873	12152498751
11	1.0000	7541	4532164	1.0000	364	2533175	5897570	101404487876
12	1.0000	3654	1638927	1.0000	186	1043937	2178324	0.0000
13	1.0000	5653	3232463	1.0000	254	2321744	4564893	0.0000
14	1.0000	4265	2174828	1.0000	196	1842912	3220976	0.0000
15	0.8333	5674	3194779	0.9157	278	1865922	3801891	97272514954
16	0.9602	3926	2055955	1.0000	115	2285674	3527374	56934700587
17	1.0000	5751	3284283	1.0000	253	2138289	4332271	0.0000
18	1.0000	6847	3492190	1.0000	307	1598739	3644483	0.0000
19	1.0000	4593	2063153	0.8540	232	1848307	3555276	130491091355
20	1.0000	7749	3986193	1.0000	329	2194583	4778853	0.0000
21	1.0000	3275	1586875	1.0000	128	1783404	3262279	0.0000
22	0.9584	5093	2521380	1.0000	171	2018963	3276900	0.0000
23	1.0000	4141	2042395	1.0000	149	2595173	3993814	0.0000
24	1.0000	7382	3521938	1.0000	282	3116186	5962359	0.0000
25	1.0000	4519	2849519	1.0000	178	2917029	5001942	0.0000
26	1.0000	3794	2014943	1.0000	194	2392830	3832124	0.0000
27	1.0000	6937	3429936	1.0000	312	3193548	5734739	0.0000
28	1.0000	5218	3196268	0.9263	203	2719156	4828290	29850262242
29	1.0000	5520	3392183	1.0000	149	2819186	5248377	0.0000
30	1.0000	3179	1429193	1.0000	174	1837054	3121158	0.0000
31	1.0000	7372	3736129	0.9951	318	2582572	5059212	17000000000
32	1.0000	4268	2321503	0.8607	220	1943776	3790285	123282830393
33	1.0000	6274	3422593	1.0000	396	2941893	5263723	0.0000
34	0.8117	5338	3085091	0.8991	320	2193812	4315986	51373360508
35	1.0000	3683	1583927	0.9408	274	1638909	2966288	112573262537
36	0.9550	5980	3246611	1.0000	312	2582771	4520793	0.0000
37	1.0000	4427	2381366	0.8974	185	1856277	3517825	77795431907
38	1.0000	4915	3093864	1.0000	208	2492861	4687732	0.0000
39	1.0000	3593	1386426	1.0000	159	1486439	3041502	170000000000
40	1.0000	5837	3193836	0.9615	190	2387589	4337329	38697345578
41	1.0000	4382	2287524	0.8607	220	2082820	3909096	103033981477
42	1.0000	7365	3828365	1.0000	294	2684563	5658197	0.0000
43	1.0000	5137	3193746	1.0000	231	2736252	4709579	0.0000
44	1.0000	6245	3492842	0.9393	316	2947259	5368620	17000000000
45	1.0000	4538	2385479	1.0000	212	2649473	4513765	0.0000
46	1.0000	5072	2784829	0.9098	226	2791623	5156166	26257615602
47	1.0000	3329	1693735	1.0000	184	2193639	3160891	0.0000
48	1.0000	5837	3402384	0.9753	194	2602744	4576575	38431665427
49	1.0000	5175	2392392	1.0000	201	2492193	4465822	0.0000
50	0.9824	3458	1632233	0.9324	184	1975234	3358312	79562039873
51	1.0000	7782	3918367	1.0000	352	2692027	5885819	0.0000

As reported in Table 5 and assuming variable returns to scale, Model (13) is implemented for the second stage. According to Table 5 (column 5), in stage 2, 36 out of 51 supply chains are sustainable. Among the unsustainable supply chains, supply chain 19 has the lowest sustainability score. Columns 6-8 of Table 5 show the projection points obtained from Model (13) for the integer inputs and outputs. In stages 1 and 2, 30 out of 51 supply chains are sustainable.

Regarding the specifications of the proposed models, the problem is explained concerning DMU15. The projection points obtained from Model (11) are $\tilde{x}^{(1)}_{1,15}=6146$, $\bar{x}^{(1)}_{2,15}=114.9326$, $\bar{x}^{(1)}_{3,15}=29186409.2191$, $\bar{x}^{(1)}_{4,15}=1909889.4944$, $\tilde{x}^{(2)}_{1,15}=266$, $\tilde{x}^{(2)}_{2,15}=1865910$, $\bar{x}^{(2)}_{3,15}=9759760.1573$, $\bar{x}^{(2)}_{4,15}=19524.3989$, $\bar{x}^{(2)}_{5,15}=338300.1180$, $\bar{y}^{(1)}_{1,15}=451.2079$, $\bar{y}^{(1)}_{2,15}=17621668.9438$, $\tilde{y}^{(1)}_{3,15}=2927329$, $\tilde{y}^{(2)}_{1,15}=3603102$, $\bar{y}^{(2)}_{2,15}=-7538830.3202$, $\hat{z}_{1,15}=2122680$, $\hat{z}_{2,15}=208.8660$, and $\hat{z}_{3,15}=95.6099$. Model (11) reports the projection points of integer-valued inputs and outputs as integer values. Moreover, the projection point for the undesirable output of this DMU (*i.e.*, 482) is reduced to 451.2079, something which is always true in this model. The factors of intermediate products may have decreasing or increasing values (as the output of Step 1 and the input of Step 2). The decreasing values mean that the relevant factors are dominated by the inputs of Step 2, whereas the increasing values mean that the relevant factors are dominated by the outputs of Step 1. Given the resultant projection points of this DMU, all three intermediate products have increasing values. In addition, the projection point of the first intermediate product is an integer value. Finally, the projection point of the second output of Step 2 is -7538830.3202, which is increased by 1399097.6798 from its initial value (*i.e.*, -8937928). The projection points obtained from Model (12) are $\tilde{x}^{(1)}_{1,15}=5674$, $\bar{x}^{(1)}_{2,15}=114.3333$, $\bar{x}^{(1)}_{3,15}=28915159.1667$, $\bar{x}^{(1)}_{4,15}=1896210.3333$, $\bar{y}^{(1)}_{1,15}=448.1667$, $\bar{y}^{(1)}_{2,15}=17796853.3333$, and $\tilde{y}^{(1)}_{3,15}=3194779$. Furthermore, the projection points obtained from Model (13) are $\tilde{x}^{(2)}_{1,15}=278$, $\tilde{x}^{(2)}_{2,15}=1865922$, $\bar{x}^{(2)}_{3,15}=10060501.9926$, $\bar{x}^{(2)}_{4,15}=20266.4441$, $\bar{x}^{(2)}_{5,15}=354693.4058$, $\tilde{y}^{(2)}_{1,15}=3801891$, and $\bar{y}^{(2)}_{2,15}=-8160651.7748$. According to their projection points, both Models (12) and (13) can detect the integer-valued projection points.

Resource allocation is the art of distributing resources for different purposes. To run the daily affairs of metro stations, the government wishes to allocate 1.7 trillion IRR to metro stations. Due to the scarcity of resources, a maximum of 10% can be allocated to each metro station ($r_j \leq 0.1 \times R$). Using Model (14), the last column of Table 5 shows the resources allocated to each supply chain. As is seen in Table 5, resources are allocated to only 20 supply chains. Metro stations 1 and 39 receive maximum resources. Resource leveling is performed for unsustainable metro stations. A lower bound of 1% is assumed for unsustainable DMUs ($r_t \geq 0.01 \times R$). The last column of Table 5 depicts that all unsustainable metro stations have been allocated a resource.

Models (7), (9), and (10) were employed to determine the overall sustainability and the sustainability of each division. The results can be seen in Table 6. In addition, the projection points of intermediate products can be seen in Table 6. The last column of Table 6 presents the resource allocation values obtained from Model (14). As is seen in Table 6, the overall sustainability and the sustainability of each division are smaller than or equal to the overall sustainability and the sustainability of each division obtained from Models (11)-(13). Hence, the results of Models (7), (9), and (10) can be confusing. Moreover, the values of resource allocation in Tables 5 and 6 are very different. Thus, considerable efforts should be made for correct resource allocation.

Table 6. The sustainability scores and projection points of DMUs using Models (7), (9), (10), and (14)

DMUs	Overall sustainability $(1-\eta_j^{S*})$	Sustainability $(1-\eta_j^{(1)*})$	Sustainability $(1-\eta_j^{(2)*})$	$\hat{z}_{1j}$	$\hat{z}_{2j}$	$\hat{z}_{3j}$	r_j
1	0.9208	0.9973	0.9158	2139473.4812	215.5331	95.9648	29444678608.9007
2	0.9579	1.0000	0.9036	2602962.9057	193.7766	97.3880	91663625897.139
3	0.8907	0.9427	1.0000	1512966.9428	183.8087	96.5410	170000000000
4	1.0000	1.0000	1.0000	2291763.0000	214.0000	96.0000	170000000000
5	0.9960	1.0000	0.9550	1592700.1038	223.0702	97.2698	89431055474.7062
6	0.8853	0.9019	0.9528	2369201.8015	194.1113	97.6371	28777444409.7212
7	1.0000	1.0000	1.0000	1248936.0000	197.0000	99.0000	0.0000
8	0.9422	0.8963	1.0000	2137503.5358	212.0327	95.7054	0.0000
9	1.0000	1.0000	1.0000	1529193.0000	178.0000	94.0000	0.0000
10	1.0000	1.0000	0.8571	1413947.0000	249.0000	98.0000	48933968809.4889
11	1.0000	1.0000	1.0000	3364395.0000	213.0000	95.0000	0.0000
12	1.0000	1.0000	1.0000	1134387.0000	141.0000	98.0000	0.0000
13	1.0000	1.0000	1.0000	2243149.0000	175.0000	97.0000	0.0000
14	1.0000	1.0000	1.0000	1378064.0000	246.0000	98.0000	0.0000
15	0.8428	0.8262	0.8903	2115851.1047	207.9009	96.0837	42871565510.8498
16	1.0000	0.9486	1.0000	1246287.0000	194.0000	97.0000	0.0000
17	0.8997	0.9455	0.9639	2101191.0010	201.8082	96.2355	52583743187.3269
18	1.0000	0.9580	1.0000	2045744.0000	234.0000	94.0000	0.0000
19	1.0000	1.0000	0.8294	1295482.0000	197.0000	97.0000	42622838198.4639
20	1.0000	1.0000	1.0000	2584270.0000	239.0000	94.0000	0.0000
21	1.0000	1.0000	1.0000	1478875.0000	212.0000	99.0000	0.0000
22	1.0000	0.9465	1.0000	1257937.0000	193.0000	97.0000	0.0000
23	1.0000	1.0000	1.0000	1398641.0000	185.0000	99.0000	0.0000

24	1.0000	0.9886	1.0000	2846173.0000	209.0000	96.0000	170000000000
25	1.0000	1.0000	1.0000	2084913.0000	213.0000	97.0000	0.0000
26	0.9703	1.0000	1.0000	1488838.4317	183.3108	96.7687	0.0000
27	1.0000	1.0000	1.0000	2541191.0000	185.0000	95.0000	59325146302.129
28	1.0000	1.0000	0.9121	2018917.0000	214.0000	97.0000	30907533212.563
29	1.0000	1.0000	1.0000	2429191.0000	221.0000	95.0000	0.0000
30	1.0000	1.0000	1.0000	1284104.0000	141.0000	98.0000	0.0000
31	1.0000	1.0000	0.9925	2472190.0000	182.0000	97.0000	57282502376.3178
32	1.0000	1.0000	0.8270	1494823.0000	205.0000	97.0000	69845449837.9639
33	1.0000	1.0000	0.8802	2321830.0000	186.0000	99.0000	54465614865.1203
34	0.7946	0.7986	0.8973	2052473.1931	199.7469	97.2111	17000000000
35	0.8771	1.0000	0.8944	1368279.9985	167.0815	98.0629	58176813432.0112
36	0.8940	0.9277	1.0000	2039215.5904	207.5150	98.0561	0.0000
37	1.0000	1.0000	0.8970	1382165.0000	178.0000	97.0000	31673873697.9744
38	1.0000	1.0000	1.0000	2194871.0000	213.0000	98.0000	0.0000
39	1.0000	1.0000	1.0000	943745.0000	196.0000	96.0000	33195612582.0795
40	0.9263	1.0000	0.8634	2124286.2521	210.8730	96.8781	43851487806.0806
41	1.0000	1.0000	0.8440	1493826.0000	218.0000	97.0000	40752335864.1636
42	1.0000	1.0000	1.0000	2973634.0000	201.0000	97.0000	0.0000
43	1.0000	1.0000	1.0000	1973327.0000	217.0000	95.0000	0.0000
44	0.8816	0.9680	0.8712	2358943.8258	204.0012	96.8976	77012202703.2097
45	1.0000	1.0000	1.0000	1864292.0000	175.0000	97.0000	0.0000
46	1.0000	1.0000	0.9027	2284639.0000	209.0000	98.0000	90533419210.2263
47	1.0000	1.0000	1.0000	967252.0000	193.0000	96.0000	0.0000
48	0.8820	1.0000	0.8978	2314798.6863	211.1251	96.1466	32929850838.9266
49	0.9425	1.0000	0.9204	2073559.3870	204.1763	94.6323	26596039642.771
50	0.9568	0.9623	0.9216	1439416.5936	175.4240	96.2232	40123197531.8669
51	1.0000	1.0000	1.0000	3193792.0000	218.0000	96.0000	0.0000

4.2 *Managerial implications*

Sustainable transport is becoming increasingly important in addressing the ecological, social, and economic dimensions of transport in megacities. The coordination of public and private transport is receiving significant attention from decision-makers and requires novel methods for allocating limited resources to unlimited demands based on sustainability criteria. To achieve sustainable urban mobility objectives, public transport service providers are developing performance measurement frameworks and systems based on passengers' expectations. The main objective of this study is to investigate the coordination and performance of public-private transport systems in a megacity using a novel NDEA model. The proposed model can handle different types of data, including integer data, negative data, and undesirable outputs, and can be used for sustainable resource allocation in public-private transport systems.

Coordination and sustainability measurement have been lees addressed in public-private transport and they are considered key challenges by managers and decision-makers of transportation systems. Allocating a limited budget for transport systems is another challenge for managers and decision-makers of transport systems. These challenges become more complex when it comes to the supply chain. Also, the type of data in sustainability measurement of public-private transport plays a key role in the results. In the case study, we dealt with negative and integer data. As well, the undesirable outputs were taken into account. In this paper, we measured the sustainability of public-private transport. Furthermore, projection points (sustainability goals) were determined for unsustainable DMUs. Also, the budget was allocated to different metro stations. The results showed the budget that should be allocated to each metro station. By allocating the budget, managers can improve the sustainability of transport.

This paper provides a novel method for measuring the performance and coordination of public-private transport systems in megacities. The study develops an NDEA model using DDF to measure the overall and stage sustainability of these systems. This model can also be used for sustainable resource allocation in public-private transport systems. The proposed NDEA model can handle different types of data, including integer data, negative data, and undesirable outputs, which allows for more reliable results and provides more realistic insights for managers and decision-makers of transport systems. In terms of sustainable transport, the study highlights the importance of optimal resource allocation and setting clear-cut, achievable targets to achieve sustainability goals such as reduced costs, less pollution, and increased passenger satisfaction. By adopting appropriate government policies, utilizing technology-based infrastructures, and collaborating with the public and private sectors, policymakers and managers of transport can work towards sustainable urban mobility objectives. Furthermore, the study suggests that public transport performance depends on various factors such as demographic characteristics, transport system features, services planning, resource allocation, and network design. In multimodal public transport networks, the incorporation of information flow, inter alia, and network planning play key roles. A lack of appropriate coordination among public transport sub-systems can affect the overall sustainability of the system significantly. Overall, this study provides a valuable tool for managers and decision-makers of public-private transport systems in megacities to improve performance and coordination and achieve sustainable urban mobility objectives.

The model proposed in this study for the performance measurement and coordination of public-private transport within multimodal transport networks is a significant step forward for the transportation industry. Its potential advantages are numerous, including the ability to provide detailed insights into sustainability and coordination, efficient resource allocation, and the handling of complex data sets. One of the most significant advantages of the proposed model is its ability to evaluate the sustainability and coordination of public-private transport networks operating within a supply chain. This is a critical aspect of the transportation industry, as it has the potential to enhance both the efficiency and effectiveness of these networks. By using a DDF, the model can provide detailed insights into the performance of these networks, including areas where improvements can be made to enhance sustainability and coordination. Another important advantage of the proposed model is its ability to allocate resources efficiently among DMUs. This is achieved through the use of NDEA, which allows for the optimization of resource allocation and management in a sustainable manner. The ability to allocate resources efficiently is essential for both the public and private sectors, as it can lead to cost savings and improved overall performance. The proposed model is also highly advantageous due to its ability to handle complex data sets. Many existing models are limited in their ability to account for various types of inputs and outputs, including those that are integer, negative, and undesirable. By overcoming this limitation, the proposed model can provide a more comprehensive approach to performance measurement and coordination of public-private transport networks. Finally, the proposed model has the potential to significantly advance the field of transportation by providing decision-makers with valuable insights into the sustainability and coordination of public-private transport networks within multimodal transport systems. This information can help decision-makers make more informed decisions about resource allocation and management, leading to improved overall performance and sustainability. In conclusion, the proposed model for performance measurement and coordination of public-private transport within multimodal transport networks has numerous advantages that make it a valuable resource for the transportation industry. Its ability to evaluate sustainability and coordination, allocate resources efficiently, and handle complex data sets has the potential to significantly enhance the efficiency and effectiveness of public-private transport networks within multimodal transport systems.

The proposed model has several managerial implications for decision-makers in the transportation industry. Firstly, decision-makers can use the model to gain detailed insights into the performance of public-private transport networks within a supply chain. This information can help decision-makers identify areas where improvements can be made to enhance sustainability and coordination, leading to improved overall performance and efficiency. Secondly, decision-makers can use the model to allocate resources efficiently among DMUs. This can help decision-makers sustainably optimize resource allocation and management, leading to cost savings and improved overall performance. Thirdly, decision-makers can use the model to handle complex data sets, including those that are integer, negative, and undesirable. This can provide a more comprehensive approach to performance measurement and coordination of public-private transport networks, which can help decision-makers make more informed decisions about resource allocation and management. Finally, decision-makers can use the proposed model to enhance the coordination between the public and private sectors in transport systems. By evaluating the performance of public-private transport networks, decision-makers can identify areas where coordination can be improved, leading to enhanced efficiency of transport systems. Overall, the proposed model has several managerial implications for decision-makers in the transportation industry. By using the model, decision-makers can gain valuable insights into the sustainability and coordination of public-private transport networks within multimodal transport systems, allocate resources efficiently, handle complex data sets, and enhance coordination between the public and private sectors in transport systems. These implications can help decision-makers make more informed decisions about resource allocation and management, leading to improved overall performance and sustainability of transport systems.

5. Conclusions and future research

Owing to population considerable growth and increased economic activities, air pollution, and heavy traffic have been major challenges in megacities in the last few decades. As such, public and private transport is of significant importance in megacities to transport a large number of passengers. Sustainability in transport has also received considerable attention because of its ecological, social, and economic impacts on society. The objective of a sustainable transport system is to minimize environmental problems and maximize social and economic benefits for society. In sustainable transport, the public and private sectors try to collaborate to attain sustainability goals. Thus, coordination of public-private transport and sustainability measurement as well as resource optimal allocation need to be carefully addressed and studied. In this study, we developed a model for measuring sustainability in public-private transport networks consisting of bus service providers and metro stations. The model was built based on the DDF approach in the NDEA structure and can address a variety of data types to obtain more accurate sustainability results. We also presented a resource allocation model among DMUs in public transport concerning budget limitations.

The study in question presented several significant contributions that propel the field of sustainability measurement and analysis forward. One of the study's primary accomplishments is the creation of a DDF, which is a potent tool for evaluating sustainability at both the overall and stage levels. This novel framework represented a considerable improvement over existing methods, as it provides a more comprehensive and nuanced approach to sustainability assessment across different production or development stages. Another crucial finding of the study was the formulation of an NDEA model that can handle integer and negative data and undesirable outputs. This development is critical since many current models are limited in their capacity to account for these data types, which are frequently encountered in sustainability research. By overcoming this limitation, the proposed NDEA model is a significant leap forward in the field of sustainability analysis. Additionally, the study introduces a resource allocation approach that employs the NDEA model. This approach has important implications for practical sustainability applications since it offers decision-makers a practical tool for optimizing resource allocation and sustainably. In conclusion, this study's contributions have the potential to considerably enhance our comprehension of sustainability and assist us in making better-informed decisions about how to encourage sustainable development and resource management. The development of the DDF and NDEA model, which can handle complex data sets, can significantly improve the accuracy and reliability of sustainability assessments. The resource allocation approach utilizing the NDEA model can provide practical and efficient solutions for sustainability management. These contributions have significant implications for decision-makers and practitioners in sustainability and can enable them to make more informed decisions that align with sustainability goals.

There were two major limitations in the current study. Firstly, owing to limitations in data gathering from public and private transportation units, we had to select 51 DMUs. In addition, almost all the data pertains to the economic dimension, with only one data point from the social dimension and one from the environmental. This could result in a solution that is predominantly focused on economic considerations, rather than a sustainable solution that takes into account all three dimensions. Due to the limited access to more environmental and social aspects, we do to run the model with existing data. As such a research direction could be developing a new model considering more environmental and social factors with different nature in the type of data. Another limitation in this study is that we assumed that all variables are controllable. However, in a transport system, there might be uncontrollable variables such as the size of buses or trains. As such, a research direction could be developing a novel NDEA model in the presence of uncontrollable variables. Moreover, due to a limitation in data gathering we evaluated the public-private system and allocated a budget between metro stations for only one period. However, there are conditions that the evaluation and resource allocation of the public-private system should cover several periods. Developing a dynamic NDEA model based on our developed model can be another interesting research avenue. In this paper, we addressed the coordination and performance measurement in a series structure. However, there might be transportation systems with both parallel and series structures. Developing a NDEA model to address these sorts of structures can be an interesting research topic. Furthermore, developing other NDEA models such as Russel enhanced network model and bound-adjusted measure for evaluating transportation systems is another research avenue.

Compliance with Ethical Standards:

Conflict of Interest: Authors declare that they have no conflict of interest.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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