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ORIGINAL ARTICLE

Analyzing multimodal transportation problem and its application to artificial intelligence

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Abstract

In recent decades, there has been increased interest among both transportation researchers and practitioners in exploring the application of artificial intelligence (AI) paradigms to address the real-life problems in order to improve the efficiency, safety and environmental compatibility of transportation systems. In this paper, our main interest is to solve transportation problem by considering the multimodal transport systems and then utilize it to solve neural network (NN) problem in AI. The multimodal transportation problem (MMTP) is nothing but a linear programming problem, and so it is easy to solve by any simplex algorithm. To analyze the proposed method, a numerical example is included and solving it we reveal a better impact for analyzing the real-life decision-making problems. Thereafter, we revoke our approach for solving NN problems, which enhances a connection between MMTP and NN problems. Finally, conclusion and future research directions are presented regarding our study.

Keywords Transportation problem · Multimodal system · Neural network · Artificial intelligence · Decision-making problem

1 Introduction

At the beginning of the twenty-first century, transportation professionals meet challenges to address the increasing complexity. Transportation professionals are asked to achieve the goals for providing efficient, safe and reliable transportation while minimizing the impact on the environment and communities. Few of those challenges that transportation professionals face are capacity problems, unreliability, pollution, poor safety record and wasted energy. Considering the challenges, we face the fact that transportation systems are generally complex systems containing a large number of equipments and different parties, each having different and sometimes conflicting objectives.

Transportation problem is mainly considered to minimize the transportation cost from sources to numerous destinations, satisfying source availabilities and destination demands, at early time of study in operations research (OR). A graphical network of TP is presented in Fig. 1.

In our daily-life problems, there are several decision-making problems such as fixing of cost of goods, profit for sellers and taking decisions for real-life multiple objective functions, which are generated by TP, and the classical TP is taken into account in different mathematical models. Nowadays, in the competitive market scenario, minimizing the transportation cost in business economy and in government policies is the utmost important matter.

Multimodal transportation problem (MMTP) is similar to a transportation problem with the inclusion of multiple modes of transportation (see Fig. 2). Multimodal transportation is also known as combined transportation which allows to transport the goods under a single contract, but it is performed with at least two modes of transport; the

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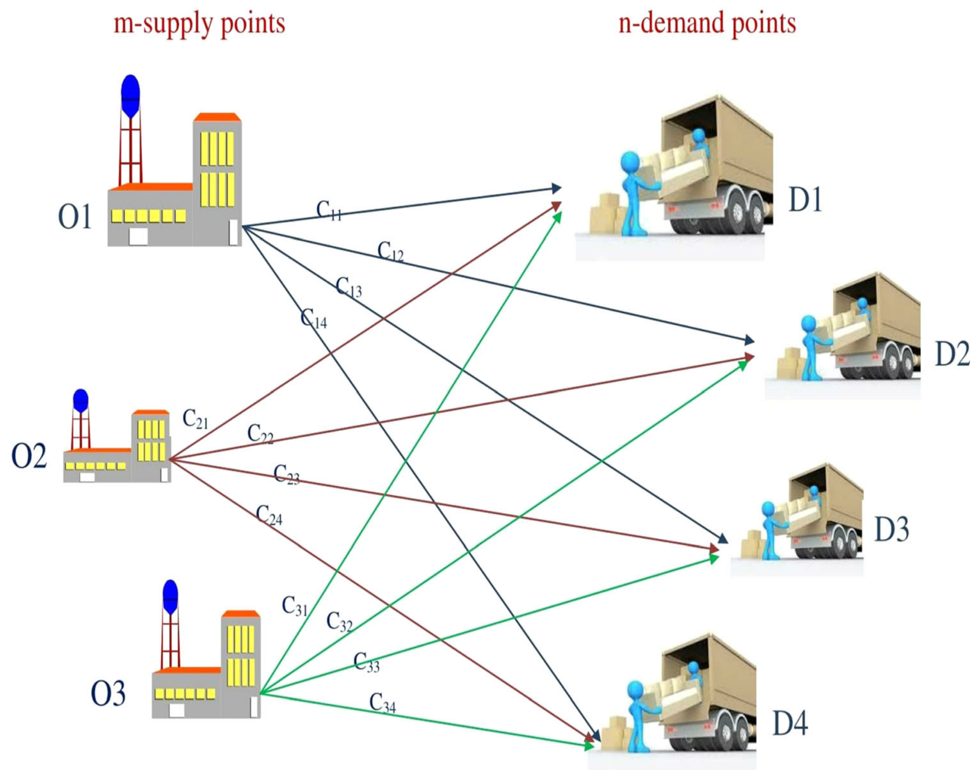


Fig. 1 Graphical network of TP

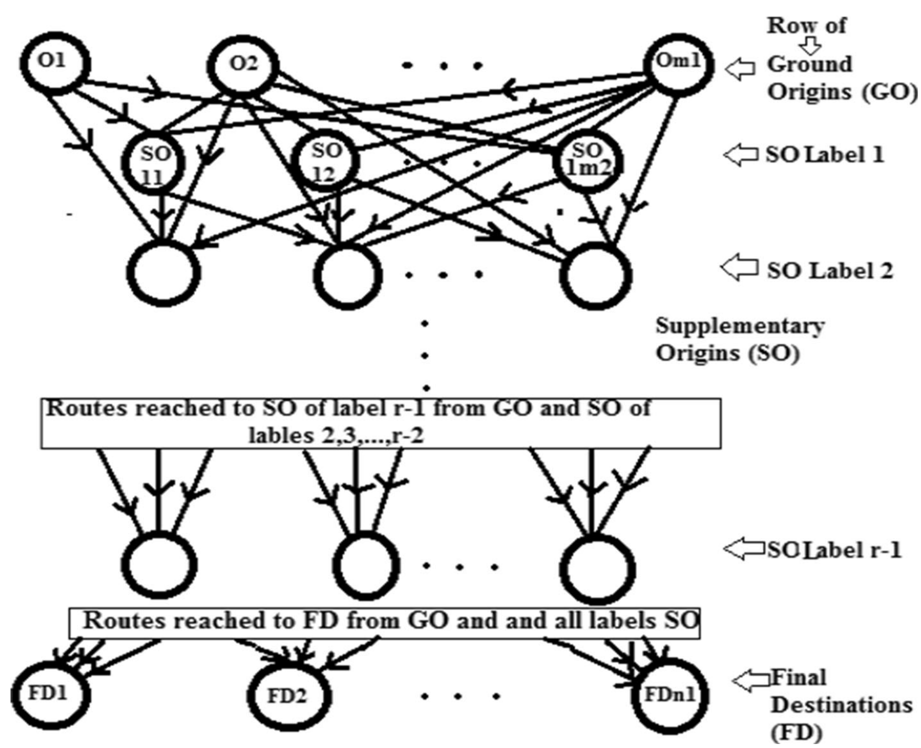


Fig. 2 Graphical representation of the MMTP

carrier is liable (in usual sense) for the whole conveyance, even though it is considered by several/different modes of transport such as road, sea and train. The carrier does not have to pose all the means of transport, and in usual practice, it is not valid. The carrier is often executed by sub-carriers which are known as actual carriers in common language. So, in a transportation system of single item of goods if more than one type of carriers are used to transport, then different types of carriers are termed as Multimodal Transport Operator (MTO).

As it is well known, neural networks (NNs) are biologically inspired systems consisting of a massively connected network of computational "neurons," organized in layers (Fig. 7). By adjusting the weights of the network, NNs can be "trained" to approximate virtually any nonlinear function to a required degree of accuracy. NNs provide typically a set of input and output layers through which the signals reach the proper destinations. Multilayer perceptron (MLP) is the most commonly used architecture of NN. The topology of a MLP is nearly same with the graphical network of MMTP. Here, we describe how the flow of information reaches the proper destination by considering the different routes (i.e., modes) of our MMTP. In this way, an interconnection between NN and MMTP is encountered.

Here, we formulate the mathematical model of MMTP by considering the multiple modes of transportation. Now, we describe the main contributions of our study as follows:

- Design a new class of TP, namely, MMTP, under the consideration of multimodal transport systems.
- On solving MMTP, we establish the superiority of our model in comparison with existing models of TP.
- Introduce the way to solve AI problem through MMTP.
- Construct NN problem and solve it through the MMTP which shows the novelty of the paper.

Therefore, the main contributions are concerned in the study by considering two different aspects: one is to build up MMTP model and another is to use it for solving AI problems. At first, the mathematical model of MMTP is described and justified by numerical example and then MMTP is used to solve NN problems in AI. The rest of the paper is organized as follows: In the next section (Sect. 2), the review of the related research is presented. We present the problem background of MMTP and its mathematical formulation in Sect. 3. To show the application of the proposed mathematical model of the MMTP, a numerical example is included in Sect. 4. The results and discussion regarding the numerical example are presented in Sect. 4.1. After that, we find a new approach to solve NN problems by MMTP in Sect. 5. A numerical example of MLP is presented to justify the effectiveness in Sect. 5.1. The conclusions with the future study are described in Sect. 6.

2 Review of related research

The basic transportation model was first initiated by Kantorovich [1], who has prescribed an incomplete algorithm for calculating the solution of the transportation problem. Hitchcock [2] studied the problem of minimizing cost of distribution of product from several warehouses to a number of purchasers. To accommodate the complexities in the real-world problems, the study on transportation problem is improved by incorporating the different mathematical models and methodologies. James et al. [3] discussed improving transportation service quality based on information fusion. A good number of research works on transportation safety planning were developed by Ergun et al. [4], Luathep et al. [5], Sheu and Chen [6]. Recently, the multi-objective transportation problem under different circumstances has been discussed by Roy et al. [7, 8], Mahapatra and Roy [9], Roy [10], Maity and Roy [11, 12].

There are several approaches available in the literature to accommodate the transportation problem through the uni-modal system. Nanry and Wesley [13] presented a detailed study on uni-modal TP. In the multimodal transportation problem, also few works have been done there, though none of these on the proposed study solve the entire logistics problem, being centered in other problems connected with MMTP or in subproblems which do not represent all the feasible restrictions. Macharis and Bontekoning [14] discussed the opportunities for OR in intermodal freight transport. The research work (Macharis and Bontekoning [14]) was reviewed on OR models which are currently used in the emerging transportation research field and define the modeling problems which need to be addressed. Eibl et al. [15] presented a study on interactive vehicle routing and scheduling software problem to a brewing company in the UK. They explained how a commercial tool was applied to schedule the day-by-day (operational) conveyance routing and scheduling to deal out the goods to the destinations. This technique was specific for the brewing problem, and the corresponding operator that controls the technique needs a previous training procedure to manage all the variables involved. In this case, the solution is quite domain-independent, with less user knowledge requirements. Catalani [16] considered a statistical study to improve the intermodal freight transport in Italy, by using the road-ship and road-train transports. Qu and Chen [17] posed the MMTP as a multi-criteria decision-making (MCDM) problem. They introduced a hybrid MCDM by considering a feed-forward artificial neural network along with the fuzzy analytic hierarchy process. The proposed case study was based on a transportation network in which nodes create terminals and edges represent distinct modes of transportation such as road, ship and train. According to the model, it can deal with several cost functions and restrictions, but they introduced six nodes, while in our proposed model there may be thousands of nodes.

Haykin [18] introduced a comprehensive foundation of NN. A study on principles of neuro-computing for science and engineering is presented by Ham and Kostanic [19].

Duda et al. [20] considered the pattern classification of NN. Omkar et al. [21] studied on multi-objective design optimization using artificial immune system. A study on solving vehicle routing problems using artificial intelligence was introduced by Tan et al. [22]. Yaghini et al. [23] introduced artificial neural network training problem. Effiti et al. [24] studied a fuzzy neural network model for solving linear programming problem under fuzzy environment. Recently, a metaheuristics approach was presented by Moghaddam et al. [25] to solve the transportation problem in fuzzy environment.

3 Necessity of MMTP and mathematical formulation

Here, we present briefly the necessity of MMTP to accommodate multiple modes of transportation in the study of linear programming problem (LPP). After that, the detailed description for formulating MMTP is presented.

3.1 Necessity of MMTP

The term *multimodal* is defined for several modes of transport in a transportation problem, and as a whole, it is referred to here as multimodal transportation problem. Generally, MMTP can be categorized as either passenger or freight oriented. Goods can be transported via several modes, and people also use different modes of transportation for their journey. Therefore, several modes of transportation are considered as follows:

- Roadway/highway automobiles (including taxi), truck, motorcycle, etc.,
- Passenger rail and traditional freight train, buses, etc.,
- Air passenger service and air freight,
- Water ferries, barges, transatlantic vessels, cruise ships, etc., and
- Bicycling, nonmotorized walking, etc.

Again, some other modes (e.g., bicycle, motorcar, etc.) are available to hold largely recreational transportation for many countries of the universe. Some of the transportation modes such as passenger airway service and rail-road communication service are very important part of the multimodal transportation system in daily life. All modes of transportation must be planned and be systematically provided similar to those of modern organizational structures (e.g., sanitation, power supplies, buildings, etc.). Not only exist the several modes, but also the transportation professionals must also plan and provide for safety and smart transfer of goods and people among different modes. This transfer is usually considered to be an intermodal transfer. Recently, James et al. [3] in University Transportation Center (UTC) defined intermodal transportation based on information fusion.

There are the important perspectives in the MMTP such as:

- To decrease total transportation costs by allowing each mode to be used for the portion of the trip in which it is the best suited,
- To increase economic productivity and effectiveness, thereby enhancing the nation's competitiveness globally,
- To reduce the overcrowding and burden on overemphasized infrastructure equipments,
- To generate higher returns from public and private investments,
- To improve mobility for the elderly, isolated, disabled and economically disadvantages, and
- Reducing energy consumption and contributing to improve air quality and environmental conditions (cf. Fox et al. [26], Veloso [27]).

Now we define three useful definitions related to our proposed MMTP.

Definition 3.1 (*Ground origin (GO)*) In a transportation problem, the sources which have the capacity for supplying the goods but do not have the capacity to gather the goods are treated as ground origins.

Definition 3.2 (*Final destination (FD)*) In a transportation problem, the destinations which have the capacity for gathering the goods but do not have the capacity to supply the goods are considered as final destinations.

There is no possibility to supply the goods according to the requirement of the *final destinations* from the *ground origins* because of that vehicle capacity/multiple routes of transport. In that case, there are required some destination nodes which have the capacity for supplying and receiving the goods simultaneously. These nodes are known as *supplementary origins*.

Definition 3.3 (*Supplementary origin (SO)*) In a transportation problem, the destinations which have the capacity for collecting the goods as well as the capacity for delivering the goods are noted as supplementary origins.

In Fig. 2, O1, O2, ..., Om1 are the *ground origins*; SO11, SO12, ..., SO1m2 are the *supplementary origins* of label 1; D1, D2,..., Dn1 are referred as the *final destinations*.

The TP under the consideration of at least one *supplementary origin* is described as the MMTP. We propose to formulate the mathematical model of the MMTP and solve it for producing a better result. To accommodate the real-life transportation problem, it is not always possible to fulfill the demand of the customers at the destination points using a single mode of transportation. Sometimes there are some restrictions for transporting the goods, and so, it is required to consider the multi-modes of transportation from different nodes. Then, the transportation is not a simple TP, which becomes a MMTP.

The mathematical model of the proposed MMTP is described in detail in the next subsection.

3.2 Model formulation

To design the mathematical formulation of classical TP, we use the following notations which are stated below:

Notations:

i: the origin/storage house,
j: the destination,
m: total number of origins,
n: total number of destinations,
C_{ij}: transportation cost per unit commodity from ith origin to jth destination,
a_i: availability of goods at ith origin,
b_j: demand at jth destination,
x_{ij}: amount of goods to be transported from ith origin to jth destination.

The mathematical model of a classical TP [2] is defined as follows:

Model 1

$$\text{minimize } z = \sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij}x_{ij} \tag{3.1}$$

$$\text{subject to } \sum_{j=1}^{n} x_{ij} \leq a_i \quad (i = 1, 2, \ldots, m), \tag{3.2}$$

$$\sum_{i=1}^{m} x_{ij} \geq b_j \quad (j = 1, 2, \ldots, n), \tag{3.3}$$

$$x_{ij} \geq 0 \ \forall \ i \text{ and } \ j, \tag{3.4}$$

The constraints (3.2) represent that the availability (chosen by decision-maker on his experience) at the origin must be greater than or equal to the amount of goods to be transported at the destinations from the origin. Constraints (3.3) represent that the amount of goods to be transported from the origins to a destination must fulfill the minimum requirement (chosen by decision-maker on his experience) at the destination. The constraints (3.4) indicate that amount of goods transported cannot be negative.

Model 1 finds optimal feasible solution, if sum of the availability of goods (in maximum) at the origins (i.e., $\sum_{i=1}^{m} a_i$) is greater than or equal to the sum of requirements (i.e., $\sum_{j=1}^{n} b_j$). Therefore, the necessary condition for obtaining the optimal solution of Model 1 is $\sum_{i=1}^{m} a_i \geq \sum_{j=1}^{n} b_j$.

In the presence of the SO in a TP, it becomes a MMTP. To formulate the mathematical formulation of MMTP, we use again the following notations which are listed as:

Notations:

m_1: the number of *ground origins (GOs)*,
n_1: the number of *final destinations (FDs)*,
m_t: the number of *supplementary origins (SOs)* at $(t-1)$th level, $t = 2, 3, \ldots, r$,
r: the number of labels for origins,
a_i^1: availability of goods at ith origin of GO,
a_i^t: availability of goods at ith origin of tth level SO, $t = 2, 3, \ldots, r$,
b_j: demand at jth node of FD,
α_1^1: a single vehicle carrying capacity from ground origins to final destinations,
α_s^t: a single vehicle carrying capacity from SO of $(t-1)$th level, $t = 2, 3, \ldots, r$, to SO of $(s-1)$th label, $s = r, r-1, \ldots, 2$,
C_{ij1}^1: transportation cost per unit commodity from ith origin to jth destination from GO to FD,
C_{ij1}^t: transportation cost per unit commodity for transportation from ith origin to jth destination from SO of $(t-1)$th level to FD where $t = 2, 3, \ldots, r$,
C_{ijs}^1: transportation cost per unit commodity for transportation from ith origin to jth destination from GO to SO of $(r-s+1)$th label, $s = 2, 3, \ldots, r$,
C_{ijs}^t: transportation cost per unit commodity for transportation from ith origin to jth destination from SO of $(t-1)$th level to SO of $(r-s+1)$th label, $t = 2, 3, \ldots, r-1$; $s = 2, 3, \ldots, r$ with $t \geq s$,
x_{ij1}^1: number of vehicles to be required for transportation from ith origin to jth destination of FD from GO,
x_{ij1}^t: number of vehicles to be required for transportation from ith origin to jth destination from SO of $(t-1)$th level to FD where $t = 2, 3, \ldots, r$,
x_{ijs}^1: number of vehicles to be required for transportation from ith origin to jth destination from GO to SO of $(r-s+1)$th label, $s = 2, 3, \ldots, r$,
x_{ijs}^t: number of vehicles to be required for transportation from ith origin to jth destination from SO of $(t-1)$th level to SO of $(r-s+1)$th label, $t = 2, 3, \ldots, r-1$; $s = 2, 3, \ldots, r$ with $t \geq s$,
z^1: objective function for minimizing transportation cost to final destination from ground origin and all supplementary origins,

z^i: objective function for minimizing transportation cost to $(r-i+1)$th label destination points from GO and all SOs of $(r-i)$th label, $i = 2, 3, \ldots, r-1$

To formulate the mathematical model of the MMTP, we consider the following steps:

Construction of objective function (z^1) for transportation to FD from GO and SO in all labels:

The transportation network corresponding to z^1 is shown in Fig. 3. Here, the routes of transportation are considered from:

GO to FD, corresponding objective function is $\sum_{i=1}^{m_1}\sum_{j=1}^{n_1}\alpha_1^1 C_{ij1}^1 x_{ij1}^1$; SO of label 1 to FD, corresponding objective function is $\sum_{i=1}^{m_2}\sum_{j=1}^{n_1}\alpha_1^2 C_{ij1}^2 x_{ij1}^2$; and so on. Finally, from SO of label $r-1$ to FD, the corresponding objective function is $\sum_{i=1}^{m_r}\sum_{j=1}^{n_1}\alpha_1^r C_{ij1}^r x_{ij1}^r$. Therefore,

$$z^1 = \sum_{i=1}^{m_1}\sum_{j=1}^{n_1}\alpha_1^1 C_{ij1}^1 x_{ij1}^1 + \sum_{i=1}^{m_2}\sum_{j=1}^{n_1}\alpha_1^2 C_{ij1}^2 x_{ij1}^2 + \ldots + \sum_{i=1}^{m_r}\sum_{j=1}^{n_1}\alpha_1^r C_{ij1}^r x_{ij1}^r.$$

In the transportation network corresponding to z^1 (cf. Fig. 3), demands at the nodes of FD need to be satisfactory. For this reason, the following constraints need to satisfy.

$$\sum_{i=1}^{m_1}\alpha_1^1 x_{ij1}^1 + \sum_{i=1}^{m_2}\alpha_1^2 x_{ij1}^2 + \ldots + \sum_{i=1}^{m_r}\alpha_1^r x_{ij1}^r \geq b_j \; (j = 1, 2, \ldots, n_1).$$

Construction of objective function (z^2) for transportation to SO of label $r-1$ from GO and SO of labels $t = 1, 2, \ldots, (r-2)$ is discussed below.

The transportation network corresponding to z^2 is shown in Fig. 4. Here, transportation may be considered as:

From GO to SO of label $r-1$, the corresponding objective function is $\sum_{i=1}^{m_1}\sum_{j=1}^{m_r}\alpha_r^1 C_{ijr}^1 x_{ijr}^1$; from SO of label 1 to SO of label $r-1$, the corresponding objective function is $\sum_{i=1}^{m_2}\sum_{j=1}^{m_r}\alpha_r^2 C_{ijr}^2 x_{ijr}^2$; and so on. Finally, from SO of label $r-2$ to SO of label $r-1$, the corresponding objective function is $\sum_{i=1}^{m_{r-1}}\sum_{j=1}^{m_r}\alpha_{r-1}^r C_{ijr}^{r-1} x_{ijr}^{r-1}$. Hence,

$$z^2 = \sum_{i=1}^{m_1}\sum_{j=1}^{m_r}\alpha_r^1 C_{ijr}^1 x_{ijr}^1 + \sum_{i=1}^{m_2}\sum_{j=1}^{m_r}\alpha_r^2 C_{ijr}^2 x_{ijr}^2 + \ldots + \sum_{i=1}^{m_{r-1}}\sum_{j=1}^{m_r}\alpha_r^{r-1} C_{ijr}^{r-1} x_{ijr}^{r-1}.$$

In the transportation network corresponding to z^2 (cf. Fig. 4), the items stored in the nodes of SO of label $r-1$ must be larger than the amount of goods transported from SO of label $r-1$ to nodes of FD. For this reason, the following constraints need to be satisfied.

$$\sum_{j=1}^{n_1}\alpha_1^r x_{tj1}^r \leq \sum_{i=1}^{m_1}\alpha_r^1 x_{itr}^1 + \sum_{i=1}^{m_2}\alpha_r^2 x_{itr}^2 + \cdots + \sum_{i=1}^{m_{r-1}}\alpha_r^{r-1} x_{itr}^{r-1} \quad (t = 1, 2, \ldots, m_r).$$

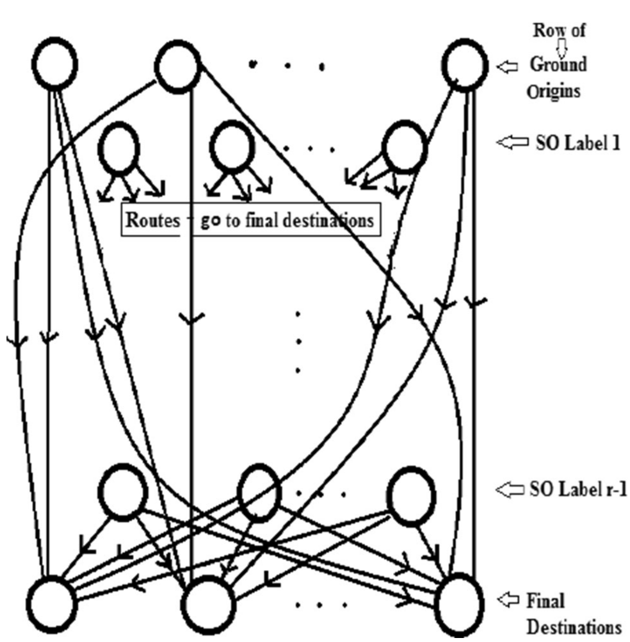


Fig. 3 Graphical representation of transportation for z^1

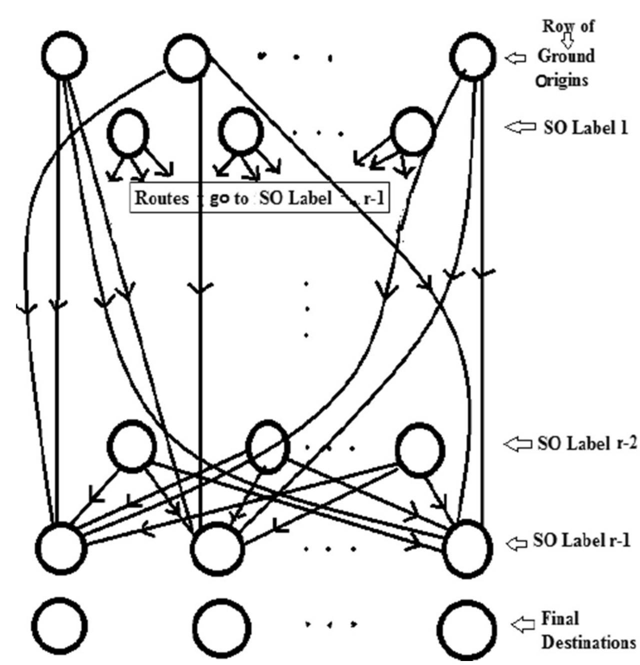


Fig. 4 Graphical representation of transportation for z^2

Again the total amount of goods stored at the nodes of SO of label $r-1$ must be lesser than its storing capacity. Therefore,

$$\sum_{i=1}^{m_1}\alpha_r^1x_{itr}^1+\sum_{i=1}^{m_2}\alpha_r^2x_{itr}^2+\ldots+\sum_{i=1}^{m_{r-1}}\alpha_r^{r-1}x_{itr}^{r-1}\le a_r^t,\ (t=1,2,\ldots,m_r).$$

In the similar way, we construct z^i $(i=2,3,\ldots,r-1)$ and finally we reach at the transportation from GO to SO of label 1.

Construction of objective function (z^r) for transportation to SO of label 1 from GO.

The transportation network corresponding to z^r is shown in Fig. 5. Here, transportation may be considered from GO to SO of label 1 and corresponding objective function is

$$z^r=\sum_{i=1}^{m_1}\sum_{j=1}^{m_2}\alpha_1^2C_{ij2}^1x_{ij2}^1.$$

In the transportation network corresponding to z^r (cf. Fig. 5), the items stored in the nodes of SO of label 1 must be larger than the amount of goods transported to SO of labels $t, t=2,3,\ldots,(r-1)$ and FD from there. So, we consider the following constraints as:

$$\sum_{j=1}^{n_1}\alpha_1^2x_{tj1}^2+\sum_{j=1}^{m_r}\alpha_r^2x_{tjr}^2+\ldots+\sum_{j=1}^{m_3}\alpha_3^2x_{tj3}^2\le\sum_{i=1}^{m_1}\alpha_2^1x_{it2}^1\quad(t=1,2,\ldots,m_2).$$

Again, the total amount of goods stored at the nodes of SO of label 1 must be lesser than its storing capacity. Therefore,

$$\sum_{i=1}^{m_1}\alpha_2^1x_{it2}^1\le a_t^2\ (t=1,2,\ldots,m_2).$$

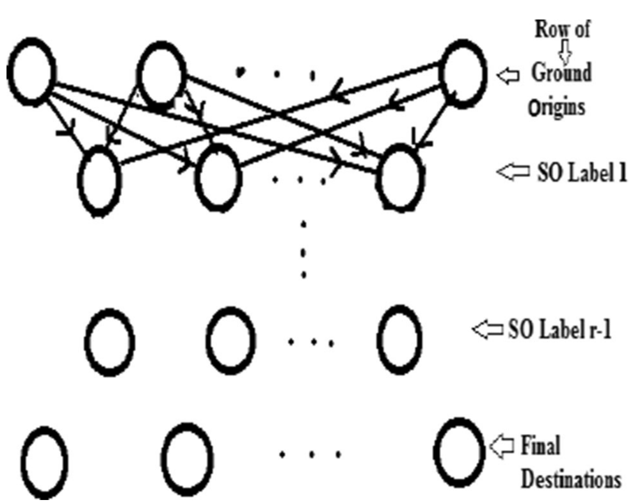


Fig. 5 Graphical representation of transportation for z^3

The complete MMTP model (see Fig. 2) is the aggregate of networks by utilizing the objective functions z^i, $i=1,2,\ldots,r$ along with the constraints required for designing the objective functions z^i, $i=1,2,\ldots,r$. Hence the mathematical model of MMTP is described as follows:

Model 2

$$\text{minimize } z=z^1+z^2+\ldots+z^r,$$

$$\begin{aligned}
z^1&=\sum_{i=1}^{m_1}\sum_{j=1}^{n_1}\alpha_1^1C_{ij1}^1x_{ij1}^1+\sum_{i=1}^{m_2}\sum_{j=1}^{n_1}\alpha_1^2C_{ij1}^2x_{ij1}^2\\
&\quad+\ldots+\sum_{i=1}^{m_r}\sum_{j=1}^{n_1}\alpha_1^rC_{ij1}^rx_{ij1}^r,\\
z^2&=\sum_{i=1}^{m_1}\sum_{j=1}^{m_r}\alpha_r^1C_{ijr}^1x_{ijr}^1+\sum_{i=1}^{m_2}\sum_{j=1}^{m_r}\alpha_r^2C_{ijr}^2x_{ijr}^2\\
&\quad+\ldots+\sum_{i=1}^{m_{r-1}}\sum_{j=1}^{m_r}\alpha_{r-1}^rC_{ijr}^{r-1}x_{ijr}^{r-1},\\
&\vdots\\
z^r&=\sum_{i=1}^{m_1}\sum_{j=1}^{m_2}\alpha_1^2C_{ij2}^1x_{ij2}^1
\end{aligned}\tag{3.5}$$

the constraints regarding availability at GO and SO of all labels

$$\text{subject to}\sum_{j=1}^{n_1}\alpha_1^1x_{ij1}^1+\sum_{j=1}^{m_r}\alpha_r^1x_{ijr}^1+\ldots+\sum_{j=1}^{m_2}\alpha_2^1x_{ij2}^1\le a_i^1\ (i=1,2,\ldots,m_1),\tag{3.6}$$

$$\sum_{j=1}^{n_1}\alpha_1^2x_{ij1}^2+\sum_{j=1}^{m_r}\alpha_r^2x_{ijr}^2+\ldots+\sum_{j=1}^{m_3}\alpha_3^2x_{ij3}^2\le a_i^2\ (i=1,2,\ldots,m_2),\tag{3.7}$$

$$\sum_{j=1}^{n_1}\alpha_1^3x_{ij1}^3+\sum_{j=1}^{m_r}\alpha_r^3x_{ijr}^3+\ldots+\sum_{j=1}^{m_4}\alpha_4^3x_{ij4}^3\le a_i^3\ (i=1,2,\ldots,m_3),\tag{3.8}$$

$$\vdots$$

$$\sum_{j=1}^{n_1}\alpha_1^rx_{ij1}^r\le a_i^r\quad(i=1,2,\ldots,m_r),\tag{3.9}$$

the constraints regarding least demands at the FD

$$\sum_{i=1}^{m_1}\alpha_1^1x_{ij1}^1+\sum_{i=1}^{m_2}\alpha_1^2x_{ij1}^2+\ldots+\sum_{i=1}^{m_r}\alpha_1^rx_{ij1}^r\ge b_j\ (j=1,2,\ldots,n_1),\tag{3.10}$$

the constraints regarding storing and distributing of goods at nodes of SO of all labels

$$\sum_{j=1}^{n_1} \alpha_1^2 x_{tj1}^2 + \sum_{j=1}^{m_r} \alpha_r^2 x_{tjr}^2 + \ldots + \sum_{j=1}^{m_3} \alpha_3^2 x_{tj3}^2 \leq \sum_{i=1}^{m_1} \alpha_2^1 x_{it2}^1 \quad (t = 1, 2, \ldots, m_2), \tag{3.11}$$

$$\sum_{j=1}^{n_1} \alpha_1^3 x_{tj1}^3 + \sum_{j=1}^{m_r} \alpha_r^3 x_{tjr}^3 + \ldots + \sum_{j=1}^{m_4} \alpha_4^3 x_{tj4}^3 \leq \sum_{i=1}^{m_1} \alpha_3^1 x_{it3}^1 + \sum_{i=1}^{m_2} \alpha_3^2 x_{it3}^2 \; (t = 1, 2, \ldots, m_3), \tag{3.12}$$

$$\vdots$$

$$\sum_{j=1}^{n_1} \alpha_1^r x_{tj1}^r \leq \sum_{i=1}^{m_1} \alpha_r^1 x_{itr}^1 + \sum_{i=1}^{m_2} \alpha_r^2 x_{itr}^2 + \ldots + \sum_{i=1}^{m_{r-1}} \alpha_r^{r-1} x_{itr}^{r-1} \leq a_r^t \; (t = 1, 2, \ldots, m_r), \tag{3.13}$$

$$x_{ijp}^{(s)} \geq 0 \; \forall \; i, j, s \text{ and } p. \tag{3.14}$$

Again to obtain the feasible solution of Model 2, it is essential to satisfy that the amount of goods required at the nodes of FD is less than or equal to the sum of availability at the nodes of GO. Therefore, the feasibility condition of Model 2 is considered as: $\sum_{i=1}^{m_1} a_i^1 \geq \sum_{j=1}^{n_1} b_j$.

In Model 2, the number of decision variables is $(m_1 \times m_2 \times \cdots \times m_r \times n_1)$.

The feasible region of Model 2 is constructed by considering the following assumptions:

- There are m_1 availability constraints (3.6) for the ground origins.
- There are n_1 number of demand constraints (3.7) for the final destinations.
- There are the restrictions of storing items in the supplementary origins so we introduce $(m_2 + m_3 + \ldots + m_r)$ number of inequalities form (3.8) to (3.10).
- Again the delivered amount of goods from the supplementary origins does not exceed the supplied amount of goods to the respective supplementary origins. To do this, we introduce $(m_2 + m_3 + \ldots + m_r)$ number of inequalities from (3.11) to (3.13).

Thus, Model 2 consists of $(m_1 \times m_2 \times \cdots \times m_r \times n_1)$ number of variables and $[2(m_2 + m_3 + \ldots + m_r) + m_1 + n_1]$ constraints along with the nonnegativity conditions. Here, Model 2 is a completely LPP and it can be solved by simplex algorithms like Big-M method, revised simplex method, Vogal's approximal method, etc.

Furthermore, time complexity for solving MMTP is similar to LPP. According to the study of strongly polynomial algorithm (cf., Kleinschmidt and Schannath [28]), a TP has time complexity $O(t_1 \log(t_1(t_3 + t_2 \log t_2)))$, where t_1, t_2 and t_3 stand for numbers of supply nodes, demand nodes and feasible arcs, respectively. Therefore, time complexity of the MMTP given in Model 2 is $O(t_1 \log(t_1(t_3 + t_2 \log t_2)))$; where $t_1 = m_1 + m_2 + \cdots + m_r$, $t_2 = m_2 + m_3 + \cdots + m_r + n_1$ and $t_3 = m_2 + m_3 + \ldots + m_r$. If the number of variables is increased, then one can use the software such as LINGO and MATLAB for solving Model 2.

Remark 1 In MMTP (see Fig. 2), we consider all the possible paths from upper label to lower label of transportation among GO, SO in all labels and FD. It may be happened in reality that there do not exist few routes of transportation from some nodes to some other nodes in different labels, and then there is no need for change in the model, but at the time of solving the model, we simply set "0" as the value of corresponding decision variable.

4 Numerical example of MMTP

The numerical example is presented here to justify the utility of MMTP. Assume that two supply centers of goods are, namely, A1 and A2 (ground origins), and D1 and D2 are final destinations in which a homogeneous commodity of a product is to be transported. The capacity of vehicle for delivering goods is 1000 items. So it is a problem for delivering the goods when the demands at the destinations are not multiple of 1000 items. Again, the destinations B1 and B2 can receive the goods from A1 and A2 and have the capacity to transport the goods to the final destinations D1 and D2. The goods are carried by the vehicles from B1 and B2 to D1 and D2 with the capacity of 100 items. So, again there is a problem to deliver goods when the amounts are not multiple of 100. Also consider that there is a destination C1 which can take the goods form A1, A2, B1 and B2 and supply them to the destinations D1 and D2. The transportation from the center C1 to the destinations D1 and D2 has no such vehicle capacity; i.e., any

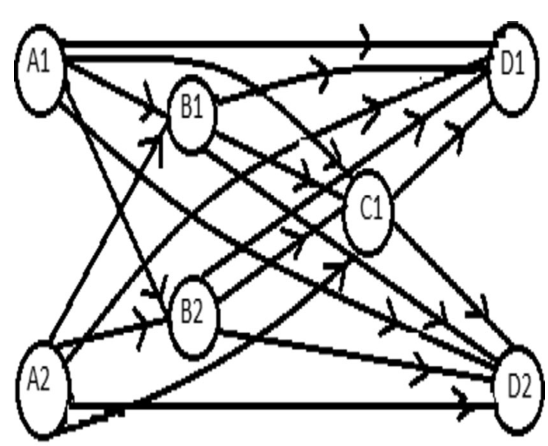


Fig. 6 Network corresponding to numerical example

amount of goods can be transported between the nodes. The graphical network corresponding to the numerical example is shown in Fig. 6. The traditional approach of transportation problem cannot be provided any such mathematical model for solving the proposed problem. Here, to solve the problem, we formulate the mathematical model which is known as MMTP.

The following notations and assumptions are considered to formulate the mathematical model of the MMTP.

- The decision variables for transporting the items are considered as follows:

  From A1 and A2 to D1 and D2 are considered as x^1_{ij1} (number of ships) using shipway with vehicle capacity $\alpha^1_1 = 1000$;

  From B1 and B2 to D1 and D2 are chosen as x^2_{ij1} (number of railway vehicles) using railway with vehicle capacity $\alpha^2_1 = 100$;

  From C1 to D1 and D2 are assumed as x^3_{ij1} (number of roadway vehicles) using roadway without any vehicle capacity restriction, i.e., $\alpha^3_1 = 1$. Since $\alpha^3_1 = 1$, here, x^3_{ij1} refers to the number of goods transported into the respective nodes.

  From A1 and A2 to C1 are taken as x^1_{ij3} with vehicle restriction $\alpha^1_3 = 500$;

  From B1 and B2 to C1 are treated as x^2_{ij3} without any vehicle restriction. Therefore, x^2_{ij3} represents the number of goods to be transported into the respective nodes.

  From A1 and A2 to B1 and B2 are considered as x^1_{ij2} and $\alpha^1_2 = 1$. Since $\alpha^1_2 = 1$, here, x^1_{ij2} refers to the number of goods transported into the respective nodes.
- The feasibility of the numerical example consists of the following number of constraints:

  The supply capacities at the ground origins A1 and A2 are introduced by two constraints. The demands at the final destinations D1 and D2 are considered by two constraints. Storing capacities at the supplementary origins B1, B2 and C1 provide three constraints. Three constraints are required to represent that the amount of goods distributed from the SOs, i.e., B1, B2 and C1, does not exceed the amount of items stored there. Hence, the number of constraints for MMTP model in the numerical example is 10.

The transportation costs in different routes are represented in Tables 1, 2, 3, 4, 5 and 6.

Again according to the decision-maker's experience, it is noted that the availability of goods at each of the GOs, A1 and A2, is 1600 items. The maximum capacity of storing at the SOs: B1, B2 and C1, is 1200 items, 1300 items and 1000 items, respectively. The mathematical model is designed based on the available data described in Tables 1, 2, 3, 4, 5 and 6 as follows:

Table 1 Transportation cost/item from A1 and A2 to D1 and D2 (in \$)

	$D1$	$D2$
$A1$	15	13
$A2$	15	18

Table 2 Transportation cost/item from B1 and B2 to D1 and D2 (in \$)

	$D1$	$D2$
$B1$	8	10
$B2$	9	7

Table 3 Transportation cost/item from C1 to D1 and D2 (in \$)

	$D1$	$D2$
$C1$	6	5

Table 4 Transportation cost/item from A1 and A2 to C1 (in \$)

	$C1$
$A1$	11
$A2$	12

Table 5 Transportation cost/item from B1 and B2 to C1 (in \$)

	$C1$
$B1$	8
$B2$	9

Table 6 Transportation cost/item from A1 and A2 to B1 and B2 (in \$)

	$B1$	$B2$
$A1$	5	4
$A2$	6	5

Model 3

$$
\begin{aligned}
\text{minimize } & z = z_1 + z_2 + z_3,\\
\text{subject to } & z_1 = 1000(15x^1_{111} + 13x^1_{121} + 15x^1_{211} + 18x^1_{221}) + 100(8x^2_{111}\\
& + 10x^2_{121} + 9x^2_{211} + 7x^2_{221}) + 6x^3_{111} + 5x^3_{121},\\
& z_2 = 500(11x^1_{113} + 12x^1_{213}) + 8x^2_{113} + 9x^2_{213},\\
& z_3 = 5x^1_{112} + 4x^1_{122} + 6x^1_{212} + 5x^1_{222},\\
& 1000(x^1_{111} + x^1_{121}) + 100x^1_{113} + 500(x^1_{112} + x^1_{122}) \le 1600,\\
& 1000(x^1_{211} + x^1_{221}) + 100x^1_{213} + 500(x^1_{212} + x^1_{222}) \le 1600,\\
& 1000(x^1_{111} + x^1_{211}) + 100(x^2_{111} + x^2_{211}) + x^3_{111} \ge 1555,\\
& 1000(x^1_{121} + x^1_{221}) + 100(x^2_{121} + x^2_{221}) + x^3_{121} \ge 1575,\\
& x^1_{112} + x^1_{212} \le 1200,\\
& x^1_{122} + x^1_{222} \le 1300,\\
& 500(x^1_{113} + x^1_{213}) + x^2_{113} + x^2_{213} \le 1000,\\
& x^1_{112} + x^1_{212} \le 100(x^2_{111} + x^2_{211}) + x^2_{113} + x^2_{213},\\
& x^1_{122} + x^1_{222} \le 100(x^2_{121} + x^2_{221}) + x^2_{123} + x^2_{223},\\
& 500(x^1_{113} + x^1_{213}) + x^2_{113} + x^2_{213} \le x^3_{111} + x^3_{121},\\
& x^p_{ijk} \ge 0 \text{ (all are taken integers)}; \forall i, j, k, p.
\end{aligned}
$$

Model 3 is completely a LPP which can be solved by any simplex algorithm. As Model 3 contains the large number of variables, we use LINGO software to obtain the solution of Model 3.

4.1 Results and discussion

Using LINGO iterative scheme, Model 3 provides the minimum value of the objective function, i.e., $z = \$41{,}700$ (sum of the values of z_1, z_2, z_3). The optimal solution of Model 3 is shown in Table 7.

In the optimal solution, the amounts of transported goods stored at all SOs and FDs are presented in Table 8.

In classical TP, there are only two types of nodes, namely supply node and demand node. In addition to that, there is at least one supplementary origin node which is presented in the MMTP. Sometimes, there are restrictions for transporting the goods between the nodes due to vehicle capacity. So, to minimize the transportation cost for delivering the goods in proper node, different types of vehicles are required.

To justify the efficiency of the proposed mathematical model of the MMTP, we describe the various possibilities in connection with the numerical example as follows:

- Consider that the routes between the supply points, A1 and A2 to FDs, D1 and D2 are seaway. A large amount of goods is delivered through a ship which is taken as 1000 items/ship. In that situation, if there are no other nodes available like B1, B2 and C1, then the formulated TP is a classical TP. In this case, we see that there exists a feasible solution of the proposed problem, but the transportation cost is not minimized. Because in each destination the minimum requirements are 1555 items and 1575 items of goods which means at least two ships are required for delivering the goods in each of the nodes D1 and D2, traditional TP is not enough to give definite conclusion without considering the SOs as we consider in our proposed study.

Table 7 Solution of Model 3

Transportation to the nodes	Value of decision variables
D1 and D2	$x^1_{121} = 1, x^2_{111} = 12, x^2_{211} = 3, x^2_{221} = 6, x^3_{111} = 55$; Rest are zero
C1	$x^2_{213} = 55$ Rest are zero
B1 and B2	$x^1_{122} = 600, x^1_{212} = 1200, x^1_{222} = 355, x^1_{112} = 0$

Table 8 Amounts of transported goods stored at all SOs and FDs

Node	B1	B2	C1	D1	D2
Value	1200	955	55	1555	1600

- Again, we assume that there is a connection through railway between B1 and B2 to D1 and D2. Then, the capacity of transports in each time by the railway is more and we consider that at a single transport, the amount of goods needed is 100. In that situation, we solve the problem without considering the supplementary origin C1 (i.e., using the value of the variables as "0" which are taken for C1), and the total transportation cost is \$42,000. The amounts of transported goods to the nodes D1 and D2, respectively, are 1600 items and 1600 items, respectively. The amounts of goods supplied at the SOs, B1 and B2 are 900 items and 1300 items, respectively.
- In the similar way, if we formulate mathematical model without considering the SOs, B1 and C1, or B2 and C1, and then the transportation cost will be increased.

Based on our discussion, we introduce the multimodal system in TP which helps to reduce the transportation cost for delivering the goods. But, in classical TP, it is not so.

5 Solving NN problem by MMTP

Here, we describe a new way for solving AI problem, especially in the field of NN with the help of our proposed study, i.e., MMTP. Though there are different types of NN, here, we choose MLP which is the most commonly used in architecture of NN. MLP is considered as a static NN which is broadly used in several real-life transportation problems due to its simplicity and ability to accomplish nonlinear-type function approximation.

In usual sense, MLP consists of three layers which are input, hidden and output. The input layer delivers one-directional flow of information to the hidden layer and finally reaches the output layer, and then it delivers the response of the network to the input stimuli. Generally, there are three different types of neurons organized in layers to this network. The input layer consists of neurons same as the number of input variables. The neurons in hidden layer consist of one or more hidden layers, which process the information and convert it into a coded form of knowledge within the network. The selection of the number of hidden layers and the number of neurons within the system represents the accuracy and performance of the network. The output layer receives the entire flow of information as an output vector.

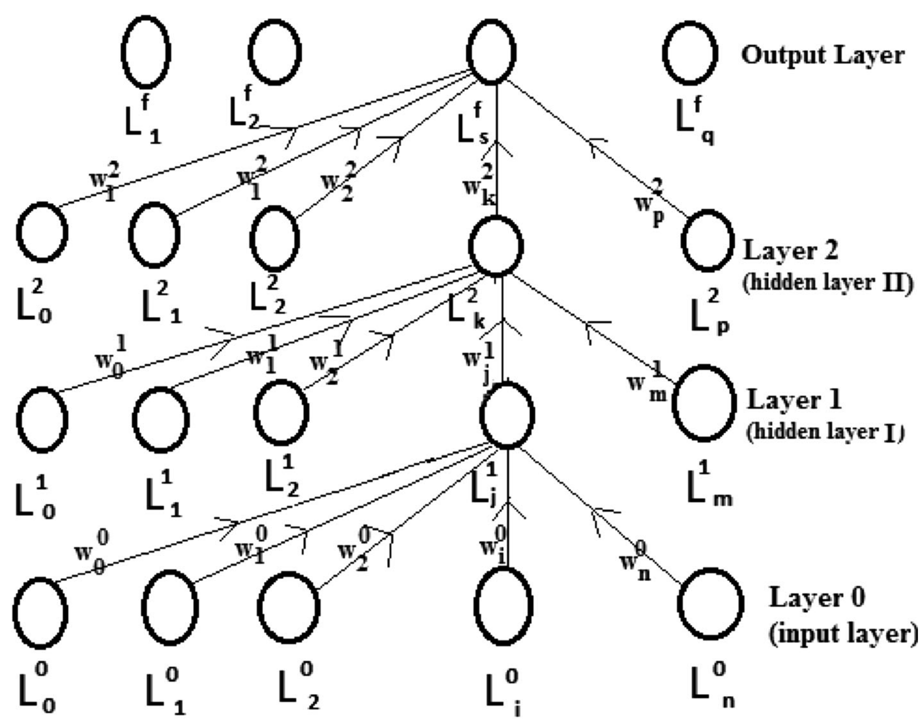
A MLP topology is shown in Fig. 7. Weighted coefficient (w_k^r) is associated with each of the connections between any two neurons inside the network. Processing of information at the neurons in each level is taken by an "activation function" which controls the result of each one. Based on the examples given in a training set, NNs train is associated with some weights. The training is continued successively until the error between the calculated and the real output over all training types is minimized. Output errors are evaluated in comparison with the desired output with the actual output. Therefore, it is possible to calculate an error function which is used to propagate the error back to the hidden layer and to the input layer in order to modify the weights. This iterative procedure is carried out until the net error evaluated in all layers to reach the signal at the output layer is reduced to a minimum value.

We relate our study of MMTP with the MLP by the following considerations:

Consider the variables (x_{ijk}^r) as the number of connections required between any two neurons in different levels in our desired network (here it is taken as MMTP). The weighted coefficient (w_k^r) is attached to the coefficient (α_k^r) in each channel. The calculated error is associated for transferring information from one layer to another layer which is taken as (C_{ijk}^r) in MLP network, and it is considered as unit cost of transportation in MMTP network. We design the constraints in accordance with the maximum amount of errors acceptable in a node of NN. If there is some difficulty for sending information from a particular layer to another layer, then the flow of information in the respective channel will be stopped, and in that case, we treat the decision variable, $x_{ijk}^r = 0$. It is similar to the situation of network MMTP, when there does not exist route between the respective nodes. With this consideration, the constraints are redesigned in the MMTP. Furthermore, the designed MMTP corresponding to MLP has polynomial complexity of time which is displayed in the last paragraph of Sect. 3.

The objective function of a NN in our MMTP is considered by the sum of errors which is minimized through our technique. Therefore, we are able to design a NN problem like MMTP and solve it by linear optimization technique presented in this paper. Basically, in usual way of AI, the error function is calculated for different possible flows of information and the best is chosen to design NNs in practical field of applications. But, this technique considers a model which calculates error functions in every possible flow of information and optimizes them, and predicts the flows in the system through a single time of calculation. To illustrate the way for solving MLP problem, here a small numerical example is presented and the usefulness is described in an efficient manner.

Fig. 7 Graphical representation of the MLP



5.1 Numerical example of MLP

Construction of a noise-free network service with ensuring minimum error in the communication system is a challenging task in the study of artificial intelligence. In Fig. 7, a numerical example of a MLP is presented. Problem is constructed with two signal-generating centers (O1 and O2) and one receiving sector (D1), so O1 and O2 are the elements of input layers and D1 is the output layer. There are two hidden layers (S1.1, S1.2, S1.3 are first hidden layer and S2.1, S2.2 are second hidden layer elements) through which the signals are passed from input layers to output layers. The possible paths of flowing signals are presented by the connecting line with the elements of the layers. The resistances are committed in the system, when the signals are passing from one node to another node through the paths. Several types of functions are used to calculate the resistances. Here, the resistances are taken as errors committed in the flow of network. To justify the effectiveness, we are not considering the functions regarding the flow of networks in several paths. We present the values of maximum error committed through the channels in Fig. 8. Furthermore, someone can select theerror functions in the formula according to his/her field of study. Now, the problem is to find the optimalpath of network flow with minimum resistances to reach signals at the output unit D1. Figure 8 shows that the presented problem is a MLP problem. Now, we formulate a MMTP model for the problem and find the optimum solution.

The MMTP model corresponding to the MLP is as follows:

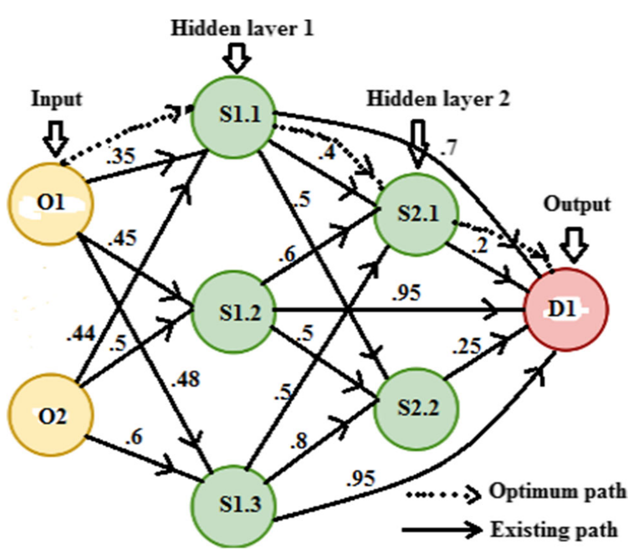


Fig. 8 Network of numerical example for MLP problem

Model 4

$$
\begin{aligned}
\text{minimize } & z = z_1 + z_2 + z_3, \\
\text{subject to } & z_1 = .7x^1_{211} + .95x^1_{221} + .95x^1_{231} + .2x^1_{311} \\
& \quad + .25x^1_{321}, \\
& z_2 = .35x^2_{111} + .45x^2_{112} + .48x^2_{113} + .44x^2_{121} \\
& \quad + .5x^2_{122} + .6x^2_{123}, \\
& z_3 = .4x^3_{211} + .5x^3_{212} + .6x^3_{221} + .5x^3_{222} \\
& \quad + .5x^3_{231} + .8x^3_{232}, \\
& x^1_{211} + x^1_{221} + x^1_{231} + x^1_{311} + x^1_{321} = 1, \\
& x^3_{211} + x^3_{212} + x^3_{221} + x^3_{222} + x^3_{231} + x^3_{232} = 1, \\
& x^2_{111} + x^2_{112} + x^2_{113} + x^2_{121} + x^2_{122} + x^2_{123} = 1, \\
& x^2_{111} + x^2_{121} = x^1_{211} + x^3_{211} + x^3_{212}, \\
& x^2_{112} + x^2_{122} = x^1_{221} + x^3_{221} + x^3_{222}, \\
& x^2_{113} + x^2_{123} = x^1_{231} + x^3_{231} + x^3_{232}, \\
& x^3_{211} + x^3_{221} + x^3_{231} = x^1_{311}, \\
& x^3_{212} + x^3_{222} + x^3_{232} = x^1_{321}, \\
& x^t_{sij} \geq 0, \ \forall t, s, i, j.
\end{aligned}
$$

Solving Model 4, we list the solution in Table 9.

We observe that minimum error communicated in the entire flow from input units to output units is 0.95. The network flow with minimum resistances to reach signals at the output unit D1 is shown by dotted lines in Fig. 8. Also, the time complexity of Model 4 is $O(t_1 \log(t_1(t_3 + t_2 \log t_2)))$, where $t_1 = 7, t_2 = 6$ and $t_3 = 8$.

Remark 2 The communicated errors due to resistances are presented by values for a simple understanding in the presented example of MLP; however, one can use respective functions in place of numerical values in the model and the functions need to be defined as constraints in proper way.

Utility of MMTP for solving NN problems:

Here, we present the effectiveness of our study for solving NN problems in the area of AI.

- The numerical example in Model 4 has been derived through MLP in Fig. 8. According to Fig. 8, researchers may attempt to optimize the neuron train through backpropagation technique or by some metaheuristic techniques. There are few drawbacks on applying the

Table 9 Solution of model 4

Objective function	Decision variables
$z = 0.95$	$x^2_{111} = 1; x^3_{211} = 1; x^1_{311} = 1;$ Rest are zero

same which are depicted below:

i. Firstly, in backpropagation technique each node has only one step length. In Fig. 8, the step lengths from input layers to output layers are 2 and 3. There are routes of passing the signals from hidden layer 1 to output layer directly without crossing through hidden layer 2. Moreover, if the error for passing signals from S1.1 to D1 is 0.5 (which is 0.7 at present), then the optimal path of network flow becomes O1 to S1.1, S1.1 to D1, which uses only two steps. In that situation, the backpropagation technique fails to judge the step length of node D1 and cannot find the optimal path using traditional backpropagation.

ii. If D1 is a workstation where ten network channels are required. Again, the input stations O1 and O2 can supply eight network channels each. Then, how many channels will be considered from O1 and O2 and corresponding optimal paths are not derivable from backpropagation technique. In this context, we need to redesign the set of constraints in MMTP Model 4, which produces the optimal solution.

iii. In most of the metaheuristic techniques, the optimal solutions are approximated and they are not exact, whereas MMTP finds exact solution. In this context, MMTP is preferable to solve the MLP problem in comparison with any metaheuristic technique.

Realizing the above factors, we conclude that MMTP is better than backpropagation or any metaheuristic technique for solving MLP in the present context.

- The problem presented in the study on a single-objective optimization problem and, however, the multi-objective optimization problem of MMTP is easy to develop and solve through Roy et al. [7, 8]. As a consequence, if there is any other objective to optimize function (such as optimize controlling cost, optimize the energy required in the system) which is conflicting objective functions of minimizing total errors, then a multi-objective programming on the MMTP provides solution of multi-objective MLP problem. Again, multi-objective MLP problem is not easy to solve by backpropagation. Therefore, the study of MMTP finds a better scope to solve MLP problem in the said ground.
- The presented model of MMTP is easy to apply for solving the problem described in shortest path computation and routing in computer networks in the study of Mustafa et al. [29]. In the study [29], simulation technique is used, but we do not need such kind of technique to solve the problem by our method.
- The presented network for solving the shortest path problem (see Thomopoulos et al. [30]) for traffic routine communication using neural network is very much similar to our MMTP network. The problem is easy to solve by our technique. Furthermore, we can employ multi-objective optimization with the same kind of problem, whereas the multi-objective concept is not possible to communicate in the technique of Thomopoulos et al. [30].

Therefore, there are many fields opened for applying MMTP in the areas of artificial intelligence optimization problem.

6 Conclusion

The main significance of this paper is broadly divided into two parts. Firstly, a new class of TP under multimodal system, termed as MMTP, has been defined, and secondly, a new approach for solving NN problem in the field of MLP by MMTP has been incorporated. Recalling the reality, it is observed that there are many situations in a transportation system in the presence of multiple modes of transportation in which the traditional TP fails to formulate a mathematical model and find the least-cost route of transportation. In this context, our proposed model MMTP has been applied to formulate the mathematical model under multiple modes of transportation and its solution provided decisions to select the mode of transportation as well as optimal solution of the problem. The results of the numerical example of MMTP presented in the paper justify the efficiency of the mathematical model MMTP. Furthermore, we have discussed a new approach to solve a NN problem in the field of MLP by MMTP. The applicability and utility of the approach have been illustrated by a numerical example of MLP problem. In this regard, this study has made a bridge between the two distinct areas, namely transportation problem and artificial intelligence in the field of operations research.

We must indicate that in relation to this paper, there are other research works of absolute relevance and importance that we have not raised because they are outside the main objectives initially set; however, in future investigation, multimodal transportation planning should be integrated in several areas such as networks, stations, user information and fare payment systems. In the same way, possibility of using MMTP for solving multi-constraint shortest path problems (Zhang et al. [31]) is an interesting line to be explored in forthcoming paper(s). Furthermore, the study MMTP may be considered for selection of modes in variety of transportation improvement policies such as mobility management strategies, pricing reforms and smart growth land use policies, etc. Besides, it is of utmost importance to think about real-world problems in this context (cf. [32, 33]), to see that we have problems with large dimensions where it is possible to apply our presented technique for getting fruitful results. In this regard, a line of research that we intend to explore in the future is the application of MMTP to solve real-life network optimizing problems under several uncertain environments, such as fuzzy, stochastic and rough.

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