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Multi-objective optimisation model under multiplex weighted drivers' collaboration network: Risk, time and profit management perspectives

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ABSTRACT

This study aims to devise a multi-objective optimisation model through the use of drivers' information diffusion capacity in transportation service procurement [TSP]. In this model, in addition to the profit optimisation of transportation companies, the allocation of freights to the most suitable drivers in the shortest possible time is considered. First, driver-to-driver interactions are modelled on a weighted drivers' collaboration network and an overlapping community detection algorithm is used to identify the communities' leaders and their drivers. Also, an objective function is developed to optimise the speed of order allocation to drivers in communities. To reduce the risk of losing customers, the *VIKOR* method is developed for ranking and allocating shipping orders to the most qualified drivers. This optimisation model enables us to simultaneously manage the three factors of time, cost, and suitability of drivers in allocating shipping orders to drivers. By solving this model, the results show novice companies tend to allocate orders to drivers in the shortest time, but well-known companies are willing to assign the orders with the lowest cost. Therefore, the results reflect the real behaviour of the TSP system, and companies can adopt policies corresponding to their risk level in allocating orders to drivers.

1. Introduction

Transportation science centres on fundamental theories, coupled with observational and experimental investigations of transportation, logistics phenomena, and their planning, design, and analysis processes. The most recent published papers in this field stated that the transportation science allows shippers to extract the most effective wages for their shipping orders by establishing a competition scheme among their drivers as carriers via bidding in the TSP system. Their bids must be such that drivers could win the auctions in exchange for acceptable profits (Lafkihi et al., 2017). This issue is vital to ensure the healthy performance of the system (Badiee & Ghazanfari, 2018).

One of the significant issues in TSP auctions is time management. Transportation companies seek to maximise the customer satisfaction by assigning their customers' freight shipping orders to drivers in the shortest possible time, which can probably reduce the profitability of companies or the satisfaction of customers. Allocating a freight shipping order to a known driver who charges a high fee leads to a reduction in profit (Badiee & Ghazanfari, 2019). But the selection of unsuitable, inexperienced, and inefficient drivers leads to dissatisfaction, that imposes excessive costs on companies, in the long run. Therefore, it is necessary to consider two vital factors; cost and risk of the driver selection, along with another factor, time management by the companies. Numerous articles, are mentioned in the literature review, have considered the two factors of time and cost in the TSP problem, but few studies investigated the social interactions of drivers, as well as the impact of driver-to-driver communications on the above factors and improving the performance of allocating shipping orders (Badiee et al., 2022). These studies by identifying driver-to-driver communications, evaluated the influences of drivers on each other, in issues such as; "accepting or rejecting shipping orders" or "diffusing shipping order news into other drivers".

An illustration of a social network in transportation structures is a group of drivers' collaboration network, whose nodes are drivers and edges are the proposed interactions between them, primarily dependent on the bass diffusion model (Chen et al., 2014) in transportation frameworks (Badiee et al., 2020). Furthermore, drivers with the same characteristics (freight shipping on a common route, from a common origin to a common destination, on a shared car, etc.) form an interconnected community, commonly share and diffuse information into

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others. First, by accurately discovering the drivers' communities and extracting the requirements of each community, the government can customized information and news and also share these with that community or make policies tailored to the requirements of each community. For instance, in the community of drivers of the freight fleet of Bandar Abbas in Iran, which has a large number of applicant drivers, the shipping rate is slightly low, predetermined and not competitive. In contrast, the drivers of the freight fleet of Babol in Iran primarily face the problem of the lack of drivers in the city, which will lead to a high fee for freight shipping. Thus, by figuring out and identifying these two types of driver communities, the government can design customized policies and decisions for each of them. In this way, the drivers of each community will only receive information related to their community and will only diffuse it within their community. In addition to reducing the shipping company's costs in allocating freight shipping orders, this will increase the productivity of the order allocation process in the TPS problem and avoid killing time in finding unsuitable drivers.

By detecting and predicting the behaviours of community drivers, companies will be able to use drivers with the ability to handle high information diffusion in the community when there is a need for rapid information diffusion, or in other cases, drivers with a low level of communication or drivers with a high possibility of accepting shipping orders in that community to be employed (Agha Mohammad Ali Kermani et al. 2016). Thus, the prediction of drivers' behaviour in a community provides shipping companies with the capacity to manage the flow of information within each community, based on their policies, an issue that has not been considered in previous studies.

Most of the studies in the field of the TSP are based on spatial information about the facility, and few studies have paid attention to the human role of drivers in this field. Drivers play a key role in the TSP system in terms of transporting goods, generating traffic flow, and communicating with other actors in the system. Therefore, overlooking the drivers could take the model away from the real space of the system. Few studies have modelled the TSP using such a concept. Badiee et al. (2020) introduced the concept of the role of a human being as an individual, capable of sharing information through collaborations, in drivers' collaboration networks without mathematical programming.

In this study, to model social relationships among drivers, we use the graph theory, as well as the concept of the drivers' collaboration network. We also develop a multi-objective optimisation model based on diffusing shipping order news among drivers' communities, which is done by their leaders by allocating the orders to the most suitable drivers, in the shortest possible time, with the highest profit and the lowest risk level for a company. A mechanism to determine drivers' scores based on their adequacy parameters is designed to select the most suitable driver in each community. In fact, for the first time as well, the drivers' information diffusion capability is used in the TSP problem to spread the shipping order information among them in order to the performance of allocating shipping orders in the TSP system from the perspectives of profit, time, and risk. Using the information diffusion ability of drivers by considering the social connections among them and modelling these communications in the context of the drivers' collaboration network concept are the key problems addressed in this paper. In other words, most of the recent studies have examined the profit of companies in the TSP system, whereas two important issues exist, namely allocating orders to the most suitable driver in the shortest possible time, and overlooking these issues can result in customer dissatisfaction and the risk of losing the companies' customers. In this paper, in addition to company profitability, these two issues are also considered in a developed optimisation model. In this way, first, the time of allocating shipping orders to drivers is optimised by developing a new objective function based on the two issues of information receiving time interval and information diffusion possibility. Next, to reduce the risk of losing customers, an objective function for allocating shipping orders to the most suitable drivers is developed. This objective function, which is based on a set of parameters affecting drivers' suitability maximises the utility of the total competency of drivers at the time of allocating the shipping order to them by ranking drivers using the *VIKOR* index.

In summary, this study has the following innovations: Modelling the social interactions between drivers in the form of a weighted drivers' collaboration network; using an overlapping community detection algorithm to identify communities of drivers and leaders to share the shipping orders news among them; developing an objective function for ranking drivers based on their competencies to reduce the risk of losing customers; developing an objective function to maximise the speed of freight allocation to drivers in each community; and developing a multi-objective optimisation model, with a simultaneous focus on maximising company profit, maximising freight allocation speed and reducing the risk of losing customers, in the TSP system.

Also, the main findings of the paper are as follows:

- Identifying and analysing the behaviour of community drivers in diffusing shipping order news into the community, in the drivers' collaboration network.
- Deriving different scenarios for transportation companies to allocate the shipping orders to drivers according to their risk level and reputations.
- Discovering and managing the communities of drivers, in the driver collaboration network, to allocate shipping orders to them.
- Simultaneous optimising the three factors of time, cost, and suitability of drivers, in the problem of allocating the shipping orders, in the TSP problem

1.1. Research framework

Fig. 1 shows the research framework of the article. Also, the details of the framework are as follows:

- **Driver collaboration network.** The Bill of lading dataset was used to produce a two-layer driver collaboration network.
- **Community detection.** An overlapping community detection algorithm was used to identify communities in the networks.

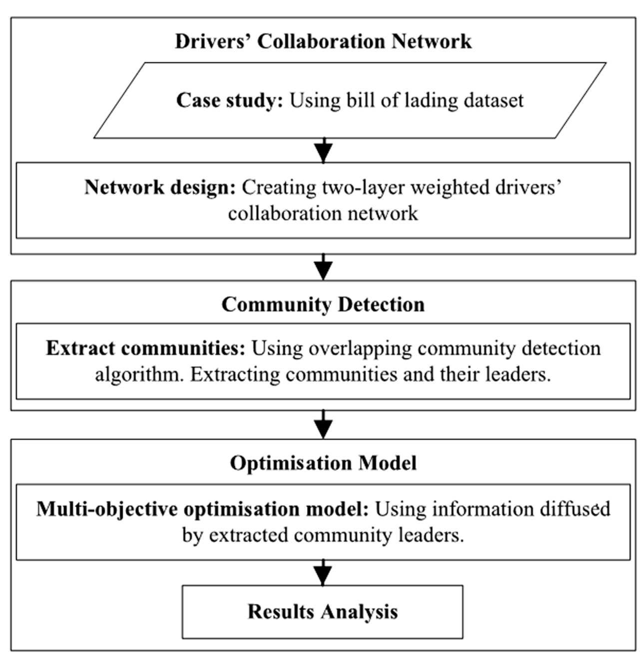

Fig. 1. The research framework.

- **Optimisation model.** Based on the information obtained from solving the community detection algorithm, a multi-objective optimisation model was developed.
- **Analysis of the results.** The case study results were evaluated and compared with the actual behaviours of the companies.

The rest of this paper is organised as follows: Section 2 investigates the relevant literature. The problem description is presented in Section 3. Section 4 covers the methodology, including the research framework, the drivers' collaboration network model, and the multi-objective optimisation model, as well as an overlapping community detection algorithm. In Section 5, a case study, along with the results of solving the community detection algorithm, as well as the multi-objective optimisation model, are presented. Finally, in Section 6, the conclusions are drawn.

2. Literature review

Regarding a transportation network, TSP has been the focus of much of the literature; in several studies, the TSP concept has been considered from various aspects, including business constraints, robust optimisations, auction mechanisms, and sustainability, as a significant function in different industries (Lim et al., 2006, 2012; Xu & Huang, 2013; B. Zhang et al., 2015). Since various transportation modes, namely road, rail, sea, and air freight, need to be addressed in depth, in the present study, we only consider the road freight TSP.

The literature has pointed out the issue of road transportation procurement from both the shipper perspective (winner determination problem), aimed at offering some bids and allocating lanes to carriers and the carrier perspective (bid generation), aimed at developing an ideal bidding strategy grounded on the analysis of the operation cost. On one hand, in road TSP systems, shippers, owners, and carriers (those carrying goods and responsible for any harm to the shipped goods) have contradictory interests. Although the shippers have aimed to decrease the costs of shipping and matching supply and demand, the carriers have been determined to increase their total revenues from shipping orders. On the other hand, the potential use of the drivers' collaboration network has not been explored adequately by shipper companies to provide high-quality service, at a good time, and with low cost and risk.

Given the vast usage of mathematical programming [MP] models in transportation systems, a few studies have investigated road TSP via MP. In cases of uncertain shipment volumes, a sampling-based two-stage stochastic programming model (B. Zhang et al., 2014) or a two-stage robust formulation (Remli & Rekik, 2013) has been developed. To increase the carrier's profit from an auction, multiple routing models have been proposed (Wang & Xia, 2005; Yan et al., 2021). To improve service quality and reduce the total cost, eight forms of the multi-objective genetic algorithm and the bi-objective branch-and-bound algorithm have been further proposed (Buer & Pankratz, 2010). A novel heuristic solution method, called the Pareto neighbourhood search, has also been developed for the bi-objective combinatorial auction model (Buer & Kopfer, 2014). Moreover, mixed-integer programming is used to acquire a multi-round combinational auction for TSP by incorporating stochastic optimisation with vehicle routing methods for carriers (Chi, 2015). Furthermore, to prevent the risk for shippers in case of shipment uncertainty, a two-stage stochastic integer programming model has been proposed for the winner determination problem (Ma et al., 2010), which has also been investigated in the context of dynamic stochastic distribution (Feki et al., 2016).

Several stochastic bid price-based optimisation models have been proposed as well (Hammami et al., 2020; Kuyzu et al., 2015; M. Rekik & Mellouli, 2012; Triki et al., 2014). For instance, an integer programming model with a single objective has been developed to lessen the total hidden and direct costs in a unified procurement auction (Othmane et al., 2014). Olcaytu proposed load-specific truckload and price-estimating methods and has examined their effects on the carriers in the transportation network in the spot truckload markets (Olcaytu & Kuyzu, 2021). Moreover, through mixed-integer programming for TSP, bidders (*i.e.* carriers) offer their best bid (*i.e.*, package) by applying bundle pricing to obtain the maximum profitability and increase their chances of winning the auction (Yan, Ma, & Feng, 2018; Yan, Ma, Xu et al., 2018). The mechanism of an integrated multi-round combinational auction has been proposed for the truckload TSP, where a winner determination problem has been solved to allocate profitable lanes to the carriers (Kwon et al., 2005). However, several non-price factors, such as familiarity with the shipper's operation, availability of suitable equipment, timely performance of carriers, as well as billing accuracy, can be pointed out as compelling issues in such problems (Jothi Basu. Bai et al., 2015), which can be referred to a multi-objective model capable of simultaneously minimising cost and maximising marketplace fairness and shipper's confidence (Ignatius et al., 2014). Full truckload TSP sustainability has also been the focus of transport logistics addressing the carrier assignment problem (Jothi Basu, Bai et al., 2015; Jothi Basu,Subramanian et al., 2015).

The delivery and pickup issues and the service time window of selective requests have also been investigated in other studies. The delivery lead time has been taken into account in a mixed-integer programming model with a single-objective function (Mamaghani et al., 2019), and a two-phase evolutionary algorithm for the bi-objective full truckload TSP, where both the transit time and the transportation cost are reduced simultaneously, has been developed (Zhang & Hu, 2019). In another study, under combinational auctions, the ideal bid-generation problem of the carrier is estimated to increase profit (Lee et al., 2007). The problem of construction bidding for heterogeneous truckload operations has further been resolved by an exact solution approach with side constraints (Rekik et al., 2017) and heuristic and exact solution methods (Hammami et al., 2019).

Given the relations between carrier and shipper decisions, bi-level programming approaches have also been considered in the literature. For instance, in combinatorial reverse auctions, a two-stage stochastic mixed-integer winner determination model has been proposed under disruption risks (Qian et al., 2020). Particle swarm optimisation models and bi-level multi-objective models, known as Discrete bi-level multi-objective particle swarm optimisation with winner determination [DBMOPSO-WD] (Yan, Ma, & Feng, 2018; Yan, Ma, Xu et al., 2018) and Multi-objective particle swarm optimisation [MOPSO] (Yan et al., 2017), have been further developed. In the TSP auction process, a bi-objective integer programming model resolved by a branch-and-bound algorithm has also been formulated (Hu et al., 2016). Consequently, reviewing the literature to find the gaps in the field of full truckload TSP (Jothi Basu,Subramanian et al., 2015) from the practitioners' perspectives could be of great importance. Table 1 illustrates the classification of the literature.

3. Problem description

One of the parameters affecting the profit of shipping companies in the TSP system is the allocation of shipping orders with lower prices (Kalantari et al., 2022). Therefore, optimisation models should be able to allocate shipping orders to drivers who are willing to accept them at lower wages. This depends on receiving price feedback from all drivers at the time of diffusing the shipping order information. Therefore, it is necessary to use the drivers' information diffusion capacity in order to spread shipping order news. Thus, the issue of information diffusion is significant in this case. However, none of the existing studies in the field of TSP systems has addressed this issue to optimise the profits of transportation companies. In this study, for the first time, the drivers' capacity to diffuse information within their communities is considered in order to optimise the performance (*i.e.*, taking profit, time, and risk into account) of allocating shipping orders in the TSP system. Shipping orders are only shared among the community leaders, to be diffused through their communities. Moreover, community leaders are determined by an overlapping community detection algorithm proposed by (Badiee et al., 2020).

In this paper, the main problem is related to the simultaneous management of time, cost, and driver selection risk in allocating freight shipping orders following the policy of shipping companies in the TSP problem. To solve this problem, for the first time, we have developed an optimisation model based on human relation intensity and the ability to diffuse information among drivers.

As mentioned, numerous studies on the development of profit maximisation models in the TSP problem have been conducted. However, none of them has considered the role of human communication among drivers in improving the productivity of the transportation system. By indicating the intensity relation and information diffusion of each driver, the positions of drivers in the transportation network are determined, which indicates their levels of experience and efficiency. The driver who has more intensity relation in the transportation network is known as an experienced driver with more information diffusion capability.

As a result, shipping companies will be able to apply the driver's position to diffuse shipping order news or to allocate shipping orders according to their policies. Moreover, quantifying the ability to diffuse information among drivers requires modelling human relations among drivers and predicting the behaviours of drivers' communities in this network, which is the basis of the behaviours of drivers' communities' prediction as the second main research problem and driver-to-driver connection modelling as the third one.

To predict the behaviours of drivers' communities, it is essential to measure and analyse two key factors: the information diffusion possibility and the information diffusion speed of drivers in communities. By finding these two factors, the behaviour of each driver in receiving shipping order news will be discovered and also predicted in terms of the possibility of accepting the order and the possibility diffusing the news or calculating its speed. Besides, the behaviour of each driver's community is derived from the behaviour of its influential drivers or leaders. For diffusing information in each community, it is also necessary to share the information with the drivers who have the highest communication ability and impact among others in their community. As a result, the importance of leaders' detection of each community and subsequently, the analysis of the possibility and the speed of information diffusion by drivers will be clear.

For this purpose, we developed a drivers' collaboration network that consists of a communication graph of drivers. The developed drivers' collaboration network is tailored to the features of the case study applied in this paper, including (I) different types of communication among drivers, (II) Relation Intensity [*RI*] among drivers, and (III) a driver's simultaneous belonging to more than one community. Based on the developed drivers' collaboration network, it will be necessary to detect significant communities of drivers. For this goal, an overlapping community detection algorithm is proposed to discover hidden patterns and meaningful groups of drivers within the drivers' collaboration network. One of the features of this algorithm is that in addition to identifying drivers' communities, influential nodes called community leaders are also identified. Community leaders are drivers who have a high ability to diffuse information within their community. Therefore, these nodes can be applied to our developed optimisation model in order to diffuse the shipping order news.

3.1. Two-layer weighted drivers' collaboration network

In order to prove the effectiveness of the proposed methodology and modelling procedure, it is obviously that the data of a real network needs to be used. Therefore, the proposed development process is taken into account for the real data of the road freight transportation system, which was previously collected by (Badiee et al., 2020). They presented a homogenous drivers' collaboration network in which graph $G = (V, E)$ is used, where V denotes a set of nodes (drivers) and E represents a set of edges (driver-to-driver connections) to introduce a single drivers' collaboration network and describe only one type of connection between drivers.

However, since the drivers have different connections in the real world, overlooking the various connections leads to losing information. Therefore, in this paper, the multiple graph $G = \langle V, E, L\rangle$, where V denotes a set of nodes, and E is a set of $\langle u, v, l\rangle; u, v \in V, l \in L, u \neq v$ that represents a kind of connection between two nodes of u and v in layer l. Besides, L indicates the type of connection between drivers in the form of a separate layer. On each layer of the network, E represents the same set of connections between drivers. For instance, E on the first layer indicates the activity of drivers in a common vehicle over a specific period, and on the second layer, it shows the drivers working together on a unique trip. Fig. 2 shows a view of a two-layer weighted drivers' collaboration network. In this figure, the weight of the edges indicates the intensity of the connection between two nodes, which can be calculated as follows:

$$RI_{uv} = R_{uv} / \sum_{i=1\dots n} R_{ui} \tag{1}$$

where R_{ui} shows the connection of node u with its neighbours, and RI_{uv} is the relation intensity value of node u with node v.

4. Mathematical model

One of the significant objectives of TSP is to assign shipping orders to the most suitable driver, in the shortest possible time and with the lowest price. In other words, on one hand, companies seek to allocate shipping orders to drivers with the lowest wages in order to maximise their profits. On the other hand, due to the importance of the issue of freight allocation time and the risk of losing customers, the companies seek to allocate shipping orders to suitable drivers in the shortest possible time. Therefore, in forming a trade-off between the two issues of time and cost of shipping order allocation, it is necessary to design a multi-objective optimisation model to consider both issues simultaneously. In this study, we develop a multi-objective optimisation model that covers objectives such as maximising company profit, maximising the speed of shipping order news diffusion, and minimising the risk of losing customers.

To develop the multi-objective optimisation model, the capacity of the drivers' collaboration network is used in this study. As mentioned earlier, the formation of the drivers' collaboration network is based on communication and interactions among drivers. Drivers have social connections with one another through their activities within the network and stimulate the information flow among them. The information flow is a major factor in the information diffusion among the drivers within their collaboration network. Therefore, the information

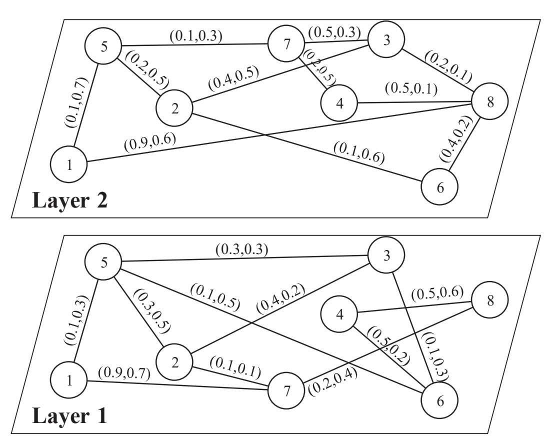

Fig. 2. Multiplex drivers' collaboration network.

diffusion feature, as an important capacity of the drivers' collaboration network, can be used to manage the network. To develop the multi-objective optimisation model, information diffusion among drivers is used in this study. Thus, the key problem of how information diffusion optimises profit and time in TSP is addressed.

In some studies, the concept of information diffusion across the network or within the communities of drivers is used to present a profit maximisation model. In these studies, there is no difference in sharing, diffusing, accepting, or rejecting information among drivers. In contrast, in social networks, people have different effects on information diffusion and have different tendencies in rejecting or accepting information. Therefore, this issue is considered in two ways when designing the multi-objective optimisation model in this study. First, shipping order news is only diffused to a certain community of the drivers' collaboration network. In other words, it is already clear that shipping order news belongs to a particular community of the network, and it will not be diffused across the whole network. This can reduce the cost of shipping order allocation. Second, shipping order news is only shared with community leaders for the diffusion of the orders among their members (followers). In practice, this increases the freight allocation speed and reduces the risk of losing customers. The realisation of this issue depends on finding community leaders, which is described in the next section.

Fig. 3 shows the condition of the problem from various dimensions. The dark sections of the figure show the situation of the present problem.

4.1. Preliminaries

The parameters and symbols used in the model are as follows:

Sets	
I	Sets of all leader members
J	Sets of all driver members
C	Sets of all communities
K	Sets of available shipping orders
Parameters	
ρ	Percentage of the commission received by the company
ε_{jc}	The threshold for accepting shipping orders by driver j in community c
V_{ck}	If shipping order k is given to community c, the value equals 1.
a_{jc}	If driver j belongs to community c, the value equals 1.
b_{ic}	If leader i is in community c, the value equals 1.
δ_c	If the news is diffused in community c, the value equals 1.
Q_j	*VIKOR* index for driver j, which is described in the next section
W_k	Approved cost for freight k
β	Cost of sharing shipping order news with a leader
d_{ij}	Distance between driver j and the selected leader i
$\widetilde{N}_{ijl}$	Ability to diffuse an order between driver i and j on the layer, which takes a fuzzy value
$\widetilde{R}_{jk}$	Cost-effectiveness of the wage for shipping order k from the driver j's point of view.
Decision variables	
Y_{jk}	The binary variable – if driver j tends to carry shipping order k, the value equals 1.
O_{ic}	The binary variable – if driver i is selected as the leader in community c_k, the value equals 1.
P_k	The company offered wage for shipping order k

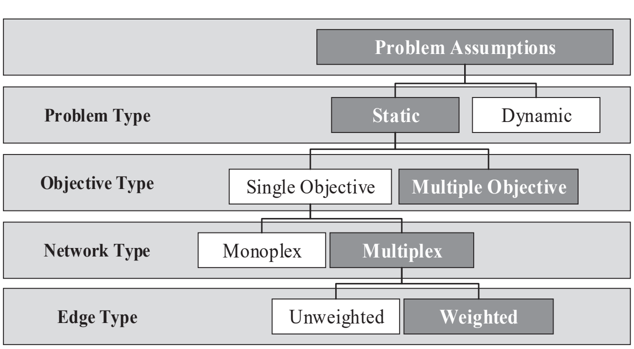

Fig. 3. Problem assumptions.

The developed multi-objective optimisation model is as follows:

$$\text{Max } Z_1 = \sum_k \sum_j \left[\rho + (1-\rho)^* \left(1 - \frac{P_k}{W_k}\right)\right] Y_{jk} - \sum_c \sum_k \sum_i \beta V_{ck} O_{ic} \quad (2)$$

$$\text{Max } Z_2 = \sum_c \sum_k \sum_i \sum_j \delta_c O_{ic} Y_{jk} V_{ck} \left(\frac{\widetilde{N}_{ij}}{d_{ij}}\right) \quad (3)$$

$$\text{Min } Z_3 = \sum_k \sum_j Y_{jk}{}^* Q_j \quad (4)$$

s.t.

$$V_{ck} O_{ic} Y_{jk} (\mu_{\widetilde{R}_{jk}}(P_k) - \varepsilon_{jc}) \geq 0 \, \forall i, k, j, c \quad (5)$$

$$\sum_k Y_{jk} \leq 1 \quad \forall j \quad (6)$$

$$\sum_j Y_{jk} = 1 \quad \forall k \quad (7)$$

$$\sum_j \sum_c Y_{jk} a_{jc} V_{ck} = 1 \quad \forall k \quad (8)$$

$$\sum_i O_{ic} = 1 \quad \forall c \quad (9)$$

$$\sum_i O_{ic} b_{ic} = 1 \quad \forall c \quad (10)$$

$$\gamma_{ik} = \sum_c O_{ic} Y_{ik} V_{ck} \; \forall i, k \quad (11)$$

$$\delta_c + \sum_i \gamma_{ik} \geq V_{ck} \quad \forall k, c \quad (12)$$

$$0.7 W_k \leq P_k \leq W_k \forall k \quad (13)$$

$$\gamma_{ik}, O_{ic_k}, Y_{jk}, \in \{0, 1\} \quad (14)$$

Eq. (2) shows the objective function of maximising the company's profit from the shipping order allocation. The first part of this function is the company's total revenue from the gained fare and the savings resulting from shipping order allocations to drivers. The second part covers the costs of sharing shipping order news with community leaders.

Eq. (3) shows the objective function of maximising the speed of freight allocation to drivers. In some cases, companies seek to reduce the freight allocation time. Using two parameters – the distance of followers from community leaders (d_{ij}) and the possibility of diffusing information $\left(\widetilde{N}_{ij}\right)$ – the objective function increases the freight allocation speed.

Eq. (4) shows the objective function of minimising the risk of losing customers due to driver inadequacy. Using this function, shipping orders are assigned to the most qualified drivers. For this purpose, the total weight of the *VIKOR* index Q_j is minimised, which is discussed in the next section.

Eq. (5) shows that if shipping order k is shared with leader i in community c, driver j will accept shipping order k when the probability of acceptance $\mu_{\widetilde{R}_{jk}}(P_k)$ is higher than the driver j's acceptance threshold. The fuzzy number related to the cost-effectiveness of accepting shipping order k is calculated, as shown in Fig. 4.

It should be noted that the news diffusion of the freight existence begins only with the communities' leaders and the threshold of acceptance of the communities' followers (ε_{jc}) corresponds to their minimum distance from their leaders, in the form shown in Table 2.

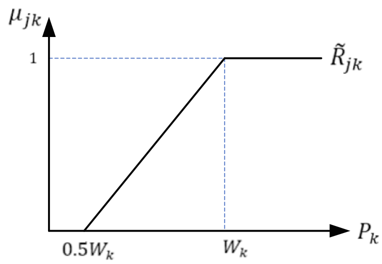

Fig. 4. The fuzzy value for the cost-effectiveness of accepting shipping order k with wage P_k.

Table 2
Information on followers' acceptance threshold ε_{jc}.

Distance from communities' leaders	Followers' acceptance threshold
1	0.7
2	0.5
3	0.4

Eq. (6) shows that driver j cannot accept more than one shipping order at a time. This means that if driver j is in service at the time of receiving shipping order k, he/she cannot accept order k, and $Y_{jk} = 0$. Therefore, if the shipping order is assigned to a driver, his/her status in all communities changes to "in service". Eq. (7) ensures that a shipping order cannot be allocated to more than one driver. Furthermore, Eq. (8) ensures that shipping order k is only assigned to one of the community drivers. Eq. (9) shows that only one leader in each community is employed to diffuse shipping order news k. Eq. (10) ensures that driver i is the leader of the intended community. According to Eq. (11), if leader i accepts freight order k in community c, the variable γ_{ik} equals 1.

Eq. (12) ensures that if a follower refuses to accept a shipping order, the order will then be allocated to one of the community leaders. Finally, Eq. (13) shows the P_k price range.

4.2. Determining drivers' scores using the VIKOR method

In TSP, a key factor contributing to a company's credibility is choosing the most suitable driver for each shipping order. Choosing the right drivers reduces the risk of losing customers. Various criteria are used to determine the right drivers. In this paper, we provide the criteria for ranking drivers, as presented in Table 3.

Based on Table 3, four criteria numbers 1, 2, 5, and 6 are qualitative and can be defined for each driver in the form of one of the linguistic variables "*Very Low*", "*Low*", "*Medium*", "*High*" and "*Very High*". Also, the fuzzy numbers related to these linguistic variables are: $VeryLow = (1,1,2)$, $Low = (1,2,3)$, $Medium = (2,3,4)$, $High = (3,4,5)$ and $VeryHigh = (4,5,5)$ corresponds to Fig. 5. Also, the two criteria number 3 and 4 are quantitative which can be extracted from the problem.

In this paper, the *VIKOR* method is used to rank drivers based on the criteria. This is a consensus method that ranks drivers by evaluating options based on the criteria and calculating the maximum group desirability and the minimum individual regret. The steps of the *VIKOR* method are as follows:

Table 3
The criteria used for ranking drivers.

No	Criteria	Type
1	Driver experience in carrying freight k	Positive
2	Driver experience in carrying freight as a single driver	Positive
3	Number of driver accidents in the last three months	Negative
4	Total working hours of a driver in the last three months	Negative
5	A driver's level of expectation from a wage received	Negative
6	Customer satisfaction with a driver	Positive

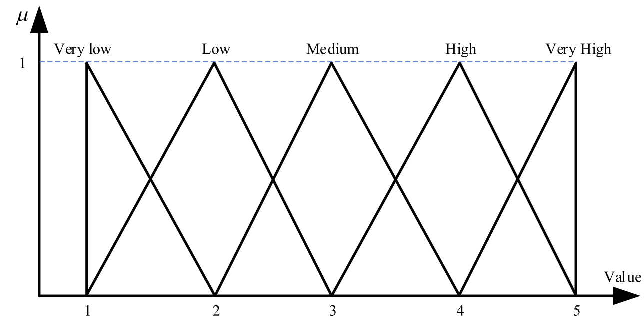

Fig. 5. The fuzzy numbers of the linguistic variables for drivers' criteria number 1, 2, 5, and 6.

Step 1. Form the Matrix of $X = (x_{ji})$, for m options and n criteria, so that the value of x_{ji} is equal to the size of i^{th} criteria for the j^{th} option.

Step 2. Determine the best and the worst values for each criterion, as follows:

$$P = \{x_1^+, x_2^+, \cdots x_n^+\} = \{min\langle x_{ji} | j = 1,2,\cdots,m \,|I \in I^-\rangle, \max\langle x_{ji}|j = 1,2,\cdots,m \,|I \in I^+\rangle\} \tag{15}$$

$$N = \{x_1^-, x_2^-, \cdots x_n^-\} = \{max\langle x_{ji} | j = 1,2,\cdots,m \,|I \in I^-\rangle, \min\langle x_{ji}|j = 1,2,\cdots,m \,|I \in I^+\rangle\} \tag{16}$$

In Eqs. (15) and (16), I^- denotes a set of negative criteria, and I^+ signifies a set of positive criteria.

Step 3. Calculate the maximum group desirability and the minimum individual regret, as follows:

$$S_j = \sum_I W_i \frac{x_i^+ - x_{ji}}{x_i^+ - x_i^-} j = 1,2,\cdots,m. \tag{17}$$

$$R_j = \max_I W_i \frac{x_i^+ - x_{ji}}{x_i^+ - x_i^-} j = 1,2,\cdots,m. \tag{18}$$

In Eqs. (17) and (18), W_i represents the standard weight of i.

Step 4. Calculate the *VIKOR* index (Q) for each option, as follows:

$$Q_j = V^*Norm(S_j) + (1-V)^*Norm(R_j), \tag{19}$$

where V denotes the weight of the two norms S_j and R_j, which is equal to 0.5.

4.3. Multi-objective model linearisation

Considering the non-linear expressions in the first and the second objective functions and the first constraint, the model presented in Section 4.1 is a non-linear integer model. In this section, these non-linear expressions are linearised by defining auxiliary variables and new relations, as follows:

$$s_{jk} = Y_{jk}P_k \tag{20}$$

$$t_{icjk} = O_{ic}Y_{jk} \tag{21}$$

$$tp_{icjk} = t_{icjk}P_k \tag{22}$$

Considering the relations created in the definition of the new variables, it is necessary to add the following constraints to the multi-objective optimisation model:

$$s_{jk} \le Y_{jk} \tag{23}$$

$$s_{jk} \le P_k \tag{24}$$

$$s_{jk} \ge P_k + Y_{jk} - 1 \tag{25}$$

$$t_{icjk} \leq Y_{jk} \quad (26)$$

$$t_{icjk} \leq O_{ic} \quad (27)$$

$$t_{icjk} \geq O_{ic} + Y_{jk} - 1 \quad (28)$$

$$V_{ck}O_{ic}Y_{jk}(2P_k - 1 - \varepsilon_{jc}) = 2V_{ck}t_{icjk}P_k - V_{ck}t_{icjk} - V_{ck}t_{icjk}\varepsilon_{jc} \quad (29)$$

$$tp_{icjk} \leq t_{icjk} \quad (30)$$

$$tp_{icjk} \leq P_k \quad (31)$$

$$tp_{icjk} \geq P_k + t_{icjk} - 1 \quad (32)$$

By adding the above constraints, the multi-objective optimisation model is modified as follows:

$$\sum_k\sum_j(Y_{jk} - \frac{s_{jk}}{W_k} + \rho\frac{s_{jk}}{W_k}) - \sum_c\sum_k\sum_i\beta V_{ck}O_{ic} \quad (33)$$

$$Z_2 = \sum_c\sum_k\sum_i\sum_j\delta_c t_{icjk}V_{ck}\left(\frac{\widetilde{N}_{ij}}{d_{ij}}\right) \quad (34)$$

Min $\sum_k\sum_j Y_{jk}{*}Q_j$ (35)

$$2V_{ck}tp_{icjk} - V_{ck}t_{icjk} - V_{ck}t_{icjk}\varepsilon_{jc} \geq 0\forall i,k,j,c \quad (36)$$

$$\sum_k Y_{jk} \leq 1\forall j \quad (37)$$

$$\sum_j Y_{jk} = 1\forall k \quad (38)$$

$$\sum_j\sum_c Y_{jk}a_{jc}V_{ck} = 1\forall k \quad (39)$$

$$\sum_i O_{ic} = 1\forall c \quad (40)$$

$$\sum_i O_{ic}b_{ic} = 1\forall c \quad (41)$$

$$0.7W_k \leq P_k \leq W_k\forall k \quad (42)$$

$$\gamma_{ik} = \sum_c t_{icjk}V_{ck}\forall i,k \quad (43)$$

$$\delta_c + \sum_i\gamma_{ik} \geq V_{ck}\forall k,c \quad (44)$$

$$s_{jk} \leq Y_{jk} \quad (45)$$

$$s_{jk} \leq P_k \quad (46)$$

$$s_{jk} \geq P_k + Y_{jk} - 1 \quad (47)$$

$$t_{icjk} \leq Y_{jk} \quad (48)$$

$$t_{icjk} \leq O_{ic} \quad (49)$$

$$t_{icjk} \geq O_{ic} + Y_{jk} - 1 \quad (50)$$

$$V_{ck}O_{ic}Y_{jk}(2P_k - 1 - \varepsilon_{jc}) = 2V_{ck}t_{icjk}P_k - V_{ck}t_{icjk} - V_{ck}t_{icjk}\varepsilon_{jc} \quad (51)$$

$$tp_{icjk} \leq t_{icjk} \quad (52)$$

$$tp_{icjk} \leq P_k \quad (53)$$

$$tp_{icjk}, P_k \geq 0 \quad (54)$$

$$tp_{icjk} \geq P_k + t_{icjk} - 1 \quad (55)$$

$$O_{ic}, Y_{jk}, s_{jk}, t_{icjk}, tp_{icjk} \in \{0,1\} \quad (56)$$

4.4. Solution approach

To solve the above multi-objective optimisation problem, first, it is necessary to classify drivers in their collaboration network into meaningful groups. Community detection algorithms have been developed to identify hidden patterns in networks. The overlapping community detection algorithm (OCDEML) proposed by (Badiee et al., 2020) is used in this paper. Some of the advantages of this algorithm include its ability to identify the optimal number of communities, find overlapping communities and detect influential nodes, called community leaders, which is suitable for our developed optimisation model. The main steps of the algorithm are as follows:

Step 1. Identify volunteer edges

By calculating the *betweenness centrality* measure for all nodes and sorting them, volunteer edges for creating local communities are identified.

Step 2. Extract local communities

Using the M modularity measure for each identified volunteer edge, a local community is created and expanded.

Step 3. Combine inner-layer communities

All local communities obtained on each layer are evaluated using the *node connectivity overlapping score* [*NCOS*] to combine and form a larger community. This criterion considers all similarities between the two communities, such as common nodes, common edges, and non-member neighbour nodes in the combination of the two communities.

Step 4. Reconstruct communities

This step uses the M modularity measure to evaluate those nodes that do not belong to any community in order to allocate them to existing communities. If the modularity value M increases as a result of adding a node to a community, the node will be allocated to the community. Finally, the nodes that do not belong to any community are grouped into outliers.

Step 5. Integrate inter-layer communities

Using the *community fitness* measure, the communities on the two layers are merged to create the final communities. This measure is calculated as follows:

$$f_{C_i}^{C_j} = \rho_{C_i+\{C_j\}} - \rho_{C_i-\{C_j\}} \quad (57)$$

where C_i and C_j represent two communities, $\rho_{C_i+\{C_j\}}$ is the redundancy value for the community C_i in case community C_j is added to it, and $\rho_{C_i-\{C_j\}}$ is the redundancy value for the community C_i in case community C_j is not added to it. If the proportion value $f_{C_i}^{C_j}$ is positive, the two communities will be merged. The iteration value ρ_c for community c is calculated as follows:

$$\rho_c = \sum_{(u,v)\in\overline{P_c}}\frac{|\{l : \exists(u,v,l) \in E\}|}{|L| \times |P_c|}, \quad (58)$$

where L represents the layers, P_c denotes the set of community edges that exist at least on one layer, and $\overline{P_c}$ signifies the set of community edges that exist on both layers.

Step 6. Extract community leaders

This step is intended to extract leaders in each community. Thus, for each node in community i, the *degree of participation* values of the node in creating the final community i (Step 5), the reconstructed communities of that final community (Step 4), its inter-layer communities (Step 3) and finally, the local communities of that community (Step 2) are calculated, respectively. By aggregating the degree of participation values, calculating the closeness centrality measure for each node, and sorting the nodes based on this measure (in descending order), the communities' leaders are determined.

5. Case study

As mentioned before, for developing the multi-objective optimisation model, the data from a study (Badiee et al., 2020) is used. This data includes the bills of lading of Iran's freight road transportation system (see Table 4). Based on this information and as shown in Table 5, the heterogeneous weighted drivers' collaboration network is designed as graph $G = \langle V, E, L \rangle$, where V denotes the set of drivers, and E represents the set of communications between drivers, where the first layer shows the shared activity in a common vehicle during a month, and the second layer indicates the common origins and destinations in more than 80 % of the drivers' trips.

Now, by solving the OCDEML community detection algorithm, the drivers' communities in the drivers' collaboration network with their community leaders are identified. Then, the obtained results are used to apply the multi-objective optimisation model.

5.1. Results from OCDEML algorithm

The results of solving the OCDEML algorithm are shown in Table 6. Based on this table, 49 final communities are identified. Moreover, 366 drivers are members of more than one community, comprising 48 % of the total drivers' network. In contrast, 704 drivers belong to only one community, and 792 drivers in the network do not belong to any community.

To diffuse shipping order news, it is necessary to determine community leaders by performing Step 6 of the algorithm. Fig. 6 shows the information on the communities' leaders for each final community in the form of a binary value. For instance, the value (33,7) indicates that 7 leaders are identified in community #33. Identifying community leaders makes it possible to share the shipping order news with them and as a result, for the leaders to diffuse the news in the community. We should evaluate when and by which possibility each community follower receives the shipping order news when it is diffused by community leaders. Therefore, it is necessary to calculate the followers' distance from their community leaders, as well as the diffusion possibility [*DP*] value of the information.

- **Distance from community leaders**

Table 4
Information on the case study.

Topic	Number
Bills of lading	1,202,756
Unique origins	1,390
Unique destinations	3,176
Total number of drivers	209,315
Total number of vehicles	103,357

Table 5
Information on the drivers' collaboration network.

Items	Layer #1	Layer #2
Nodes	1862	1416
Edges	4696	4061

Table 6
Results of the OCDEML algorithm.

Items	Value
Number of communities	49
Number of overlapping nodes	366
Overlapping nodes	48 %
Non-overlapping nodes	704
Outliers	792

The shortest path measure is used to calculate the time interval. Fig. 7 shows the distribution of community followers for the values of the shortest paths 1, 2, and 3. According to the figure, 72 % of the followers are at a distance of 1 from their community leaders. In other words, if community leaders diffuse shipping order news, on average, 72 % of the followers will receive the news. Likewise, 27 % of the followers are at a distance of 2, and only 1 % of them are at a distance of 3, which is the farthest distance from their community leaders.

- **Diffusion possibility**

Using the weight information of the edges in the drivers' collaboration network, *DP* values are calculated. For this purpose, the possible value of the *RI* between two nodes is calculated by the *minimum T*-norm operator. Fig. 8 shows the distribution of community followers based on their *DP* values. The *DP* values are shown in the Z-number format. For example, the *DP* value for community number #1 is as follows:

$$(1, [0.6, 0.7], 0.71) = Probability(Possibility(Community(\#1)) \in [0.6, 0.7])is0.71$$

In community #1, 71 % of the followers have *DP* values between 0.6 and 0.7.

By analysing Fig. 8, the distribution of the community followers with different *DP* values in receiving shipping order news can be calculated. This means that through the leaders' diffusion of the shipping order news in a community, the percentage of the followers and the *DP* values in receiving that news can be calculated. This helps us understand the concept of diffusing information in a community and its impact on community followers to model and solve the multi-objective optimisation problem.

Accordingly, Fig. 9 shows the distribution of community followers when $DP \geq 0.7$. For example, after diffusing shipping order news in community #7, about 70 % of the followers will receive the news with a *DP* value of more than 0.7.

5.2. Applying a multi-objective optimisation model based on information diffusion of leaders

To apply the multi-objective model, we use the goal programming method. In the goal programming model, the objective function (59) is a combination of the three objective functions of the model.

Minimise:

$$Z_g = \mathrm{Wg}_1\left(\frac{\mathrm{dp}_1}{\mathrm{DO}_1}\right) + \mathrm{Wg}_2\left(\frac{\mathrm{dp}_2}{\mathrm{DO}_2}\right) + \mathrm{Wg}_3\left(\frac{\mathrm{dn}_3}{\mathrm{DO}_3}\right) \quad (59)$$

Besides, the following constraints are added to constraints (36) to (56):

$$\sum_{k}\sum_{j}\left(\mathrm{Y}_{jk} - \frac{\mathrm{Z}_{jk}}{\mathrm{W}_k} + \rho\frac{\mathrm{Z}_{jk}}{\mathrm{W}_k}\right) - \sum_{c}\sum_{k}\sum_{i}\beta\, V_{ck}\mathrm{O}_{ic} + dp_1 - dn_1 = G_1 \quad (60)$$

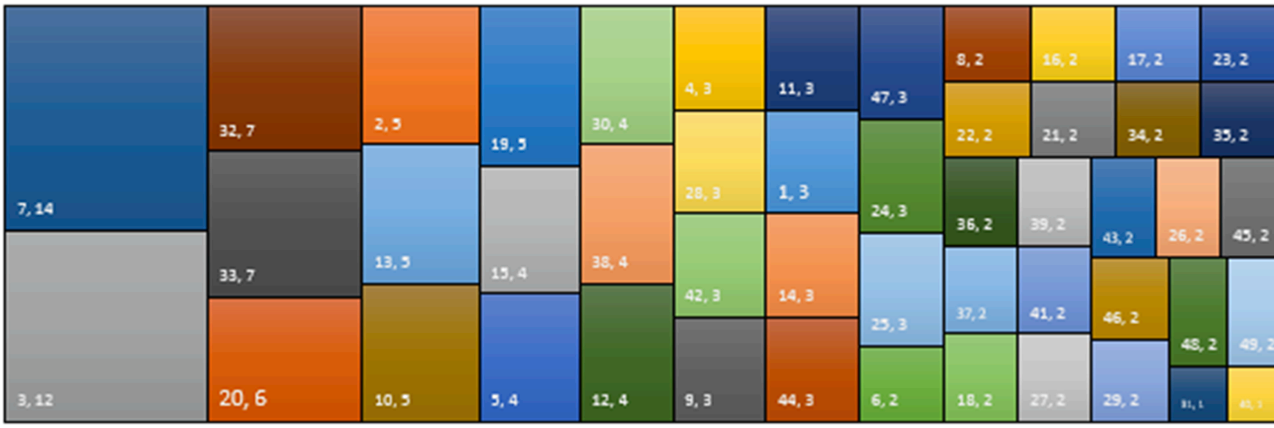

Fig. 6. The leaders of each final community.

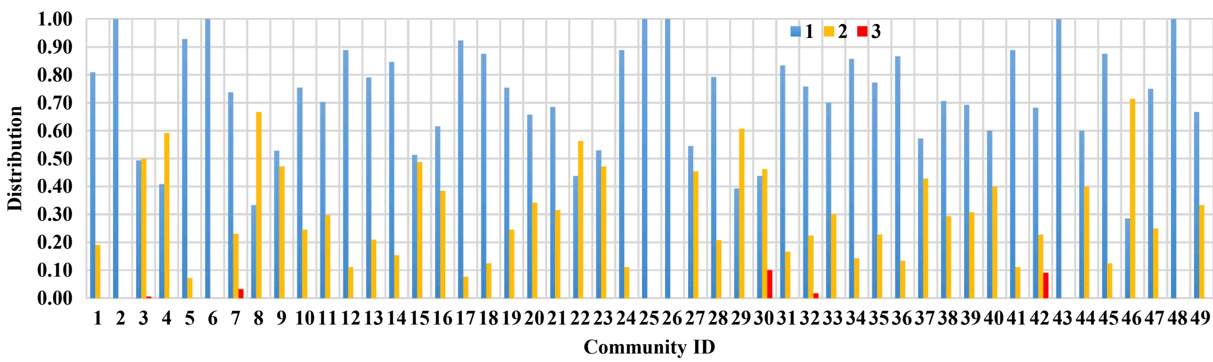

Fig. 7. The dispersion of the communities' followers, based on different values of the shortest path (when *T*-norm is the *minimum*).

$$\sum_{c}\sum_{k}\sum_{i}\sum_{j}\left[\delta_c t_{icjk} X_{ijc} V_{ck}\left(\frac{\widetilde{N}_{ij}}{d_{ij}}\right) - \delta_c u_{icjk} X_{ijc} V_{ck}\left(\frac{\widetilde{N}_{ij}}{d_{ij}}\right)\right] + dp_2 - dn_2 = G_2 \tag{61}$$

$$\sum_{k}\sum_{j} Y_{jk} * Q_j + dp_3 - dn_3 = G_3 \tag{62}$$

where Z_g denotes the goal objective function and G_{of} s represents the ideal values of the objective functions, as determined by experts. The variables dp_{of} and dn_{of} are positive and negative deviations, respectively, from the goal of each objective function. The variable Wg_{of} is the weight value of the deviation. The variable DO_{of} is the difference between the upper and the lower limits of each objective function, which is used to normalise the positive and the negative deviations in the objective function. In constraints (60) to (62), the distance of each objective function from its positive and negative deviations is equal to the ideal value of that objective function.

According to Section 4.2, six effective criteria for the reputation of a shipping company were introduced. In order to defuzzify the fuzzy numbers related to each of the criteria numbers 1, 2, 5, and 6 for each of the drivers, the α_cut value was considered to be one. The reason for choosing this value is that we are looking to extract a value in each of criteria numbers 1, 2, 5, and 6 for each driver that has the highest possibility of occurrence for that driver. Based on this, the information related to the extracted numbers for each linguistic variable along with the weight of each one is shown in Table 7.

In the mathematical modelling of the case study, there are 1072 drivers whose ranks were calculated according to simulated data (for their criteria) and also the *VIKOR* method. Fig. 10 shows the dispersion of drivers' scores. As mentioned before, to reduce the risk of losing customers, the *VIKOR* method is developed for ranking and allocating shipping orders to the most qualified drivers based on a set of parameters affecting drivers' suitability. The lower the *VIKOR* index of the desired driver, the more desirable it is compared to others according to the criteria. Therefore, Fig. 10 shows that the proposed model has a lower tendency to allocate freights to a significant number of high-risk drivers who have a *VIKOR* index higher than 0.6.

We consider the ideal objectives of g_1, g_2, g_3 as (1.625, 5000, 0), respectively, and present a sensitivity analysis with 5 different scenarios for the model. Thus, in each scenario, by changing the weights of deviations of the objective functions, the behaviour of these functions under different weights is analysed. Table 8 shows the scenario information. In designing the scenarios, we consider that the first and the third objective functions agree with the diffusion (*i.e.,* they become closer to their ideal value by increasing the information diffusion), while the second objective function opposes the diffusion (*i.e.,* the less diffusion is done in the community and the shorter the distance of the shipping orders assigned to leaders or drivers from them, the value of this objective function becomes closer to its ideal value).

Table 9 shows the optimal price for each scenario, according to the price offered by the company, in each community. In addition to determining the most suitable leader for the diffusion of the shipping order news and the order allocation to the driver, the distance of the selected driver from the leader is determined in the "Dist. from leader" column of the table.

5.3. Result analysis

Fig. 11 shows the values of the company's profit (first objective function) based on different scenarios and the final communities. According to this figure, when the weight of the objective function

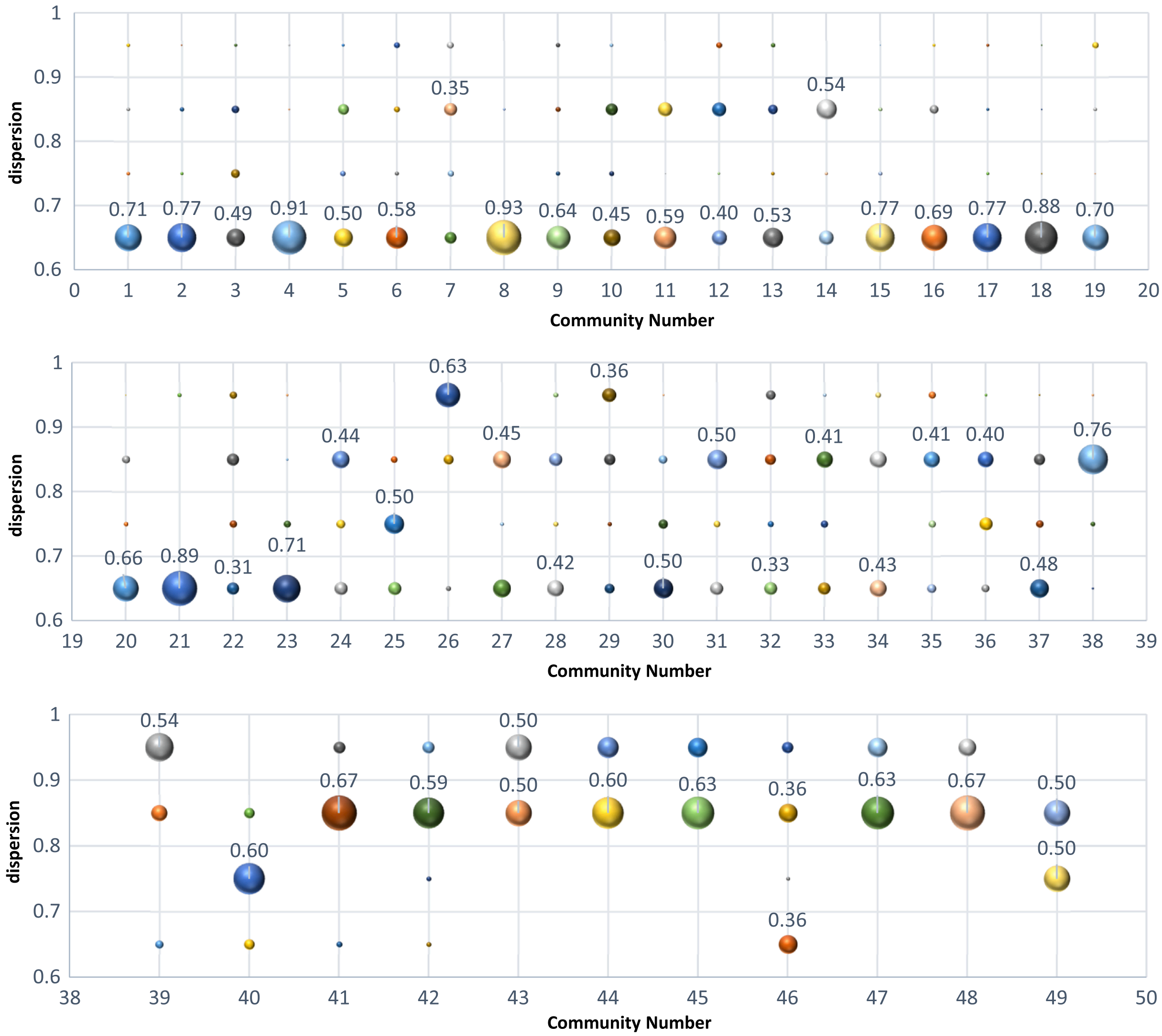

Fig. 8. The dispersion of the communities' followers, based on different *DP* values.

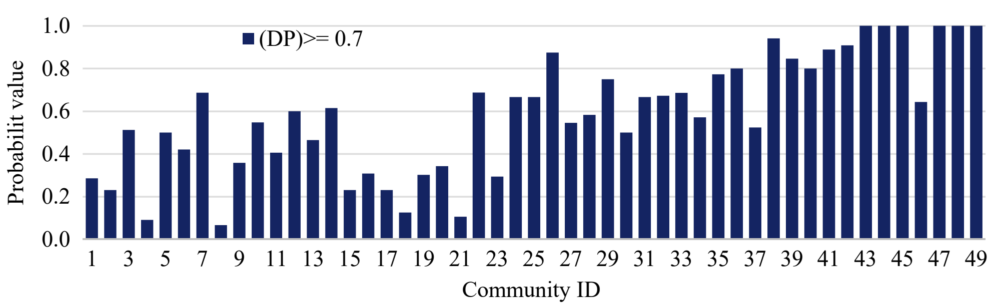

Fig. 9. The dispersion of the communities' followers in receiving shipping order news when $DP \geq 0.7$.

Table 7
The criteria values for ranking drivers.

Linguistic terms	Value	Weight
Very low	1	0.1
Low	2	0.2
Medium	3	0.4
High	4	0.2
Very high	5	0.1

decreases in the scenarios, its value decreases, too. In other words, in the scenarios with the lowest weights, meaning Scenarios 3 and 5, the company's profit is considered less important than other objective functions, and the company prefers to assign the shipping orders to the drivers in the shortest possible time. Thus, for these two scenarios, shipping orders are assigned to community leaders or followers at a shorter distance from the community leaders. Therefore, the optimal price values are considered at their highest value compared with other scenarios, which is explained in Fig. 13. As a result, the company's profit is at a lower value compared with other scenarios. In contrast, by

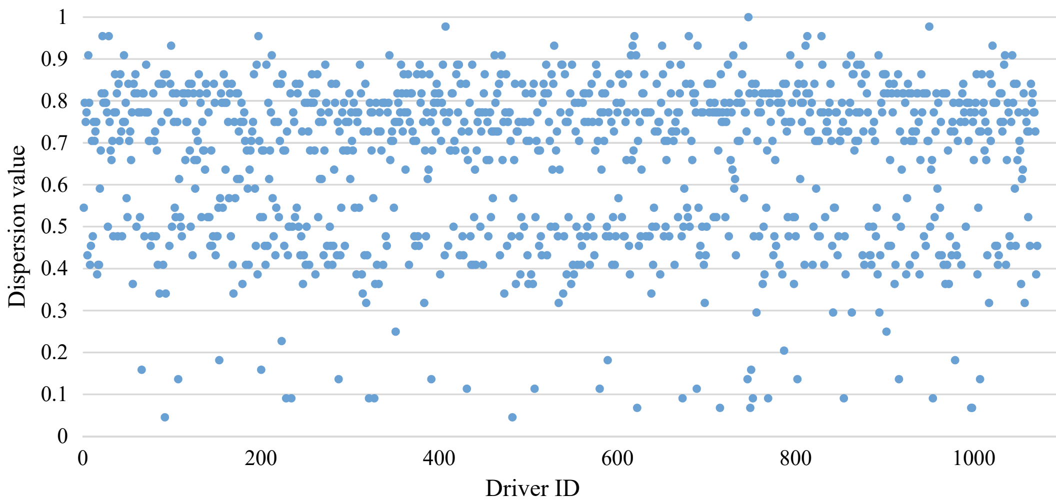

Fig. 10. The dispersion of the driver's score.

Table 8
Information on scenarios based on different weights of the objective function.

Scenarios	Wg_1	Wg_2	Wg_3
1	0.33	0.33	0.33
2	0.4	0.2	0.4
3	0.1	0.8	0.1
4	1	0	0
5	0	0	1

increasing the weight of the first objective function (*i.e.,* Scenarios 2 and 4), the value of the profit objective function is at a higher level compared with other scenarios. In this case, the company's profit is of great importance, and the company seeks to allocate shipping orders to drivers at greater distances from community leaders.

Based on this figure, the optimal values of the profit objective function can be interpreted as follows:

Peaks. These points are related to the situation in which shipping orders are allocated to followers in the depths of the community. In this case, due to the great distance of the selected followers from their community leaders, these followers accept the shipping orders at a lower price and drive the company's profit to its maximum value.

Valleys. These points are related to the situation in which shipping orders are assigned to community leaders. Because community leaders accept the shipping order at a higher price, the profit objective function is at its lowest value.

Fig. 12 shows the values of the freight allocation speed function (objective function 2) based on different scenarios and final communities. This objective function aims to reduce the time of the shipping order allocation to drivers in each community. In Scenario 3, where the weight of this objective function is 1, shipping orders are allocated to community leaders or followers at a short distance from the leaders. Therefore, this objective function is at its maximum value. This scenario is related to a situation where the company is unwilling to accept the risk of prolonging the time to find a driver and tends to allocate the shipping orders to the nearest drivers in each community in the shortest possible time. Therefore, shipping orders are allocated only to the leaders of each community. It should be noted that these leaders accept shipping orders at higher wages compared with those of other drivers. In contrast, in Scenarios 4 and 5, where the weight of the freight allocation speed objective function is zero, most of the shipping orders are allocated to followers at distances 2 and 3 from the community leaders, which causes the objective function to show its worst value. These two scenarios are related to the situation where the company can tolerate a level of risk to extend the time of the shipping order allocation in order to make more profit. Therefore, the company prefers to allocate shipping orders to drivers in the depth of the community.

Fig. 13 shows the optimal values of the approved price based on different scenarios for final communities. As illustrated in this figure, the valley points, where low prices are realised, are created based on the selection of followers at distances of 2 and 3 from community leaders. The reason is that by allocating shipping orders to followers in the depths of the community, the minimum wage value is obtained. In other words, the drivers who are in the depths of the community and far away from their leaders, due to less communication and experience, are willing to accept the shipping orders at a lower price. In contrast, the peak points in this figure show that shipping orders are allocated to community leaders or followers at a distance of 1 from the leaders. These drivers also tend to accept shipping orders at higher wages.

If a large weight is considered for the profit function (Scenarios 2 and 4), the minimum value is obtained for the optimum price. This is related to the situation where the company, due to its experience and being well-known, has a high-risk tolerance and wants to make more profit by searching the depths of communities and allocating shipping orders to followers at great distances from their community leaders. Conversely, when a company is risk-averse due to being a novice, it tends to search for community leaders or allocate shipping orders to community leaders or followers at a distance of 1 from the leaders and in the shortest possible time. In this case, risk-averse companies choose Scenarios 3 and 5, leading to higher prices compared with other scenarios.

The reason that there is a limited number of values (up to 4 values) in Fig. 11 for the values of the company's profit and the optimal price in each scenario is that, on the one hand, drivers are located in limited numbers of levels (4 levels) of communities. In other words, the drivers are either as leaders (level 0) or at a distance of one (level 1) or at a distance of 2 (level 2) or at a distance of 3 (level 3) from their community leaders. On the other hand, based on equation (2), the profit function is a function of the revenue and cost sectors. Considering that the amount of acceptance level (Table 2) is the same for each certain level of drivers, the amount of income is similar for each level. So, the diversity of the amount of income is a function of the diversity of the levels. Also, the cost part of the profit function is also a function of the number of the levels and has the same value in each driver level. Therefore, the values obtained from the profit function have a direct relationship with the number of community levels, and the maximum value is four in each scenario. This problem also applies to the speed and price value in Figs. 12 and 13.

Fig. 14 shows the combination of selected drivers in each scenario. On one hand, well-known and experienced companies tend to allocate shipping orders to drivers farther away from community leaders (risk-

Table 9
The results of applying he multi-objective optimisation model.

Community ID	Scenario 1				Scenario 2				Scenario 3				Scenario 4				Scenario 5			
	Optimum price	Leader ID	Assignee information		Optimum price	Leader ID	Assignee information		Optimum price	Leader ID	Assignee information		Optimum price	Leader ID	Assignee information		Optimum price	Leader ID	Assignee information	
			Dist. from Leader	Driver ID			Dist. from Leader	Driver ID			Dist. from Leader	Driver ID			Dist. from Leader	Driver ID			Dist. from Leader	Driver ID
1	0.95	15	0	15	0.95	15	0	15	0.95	15	0	15	0.95	283	0	283	1	15	0	15
2	0.95	11	0	11	0.95	11	0	11	0.95	11	0	11	0.95	22	0	22	1	15	0	15
3	0.95	389	0	389	0.95	389	0	389	0.95	389	0	389	0.95	44	0	44	1	389	0	389
4	0.95	12	0	12	0.95	12	0	12	0.95	12	0	12	0.95	533	0	533	1	12	0	12
5	0.95	1513	0	1513	0.75	1513	2	452	0.95	1513	0	1513	0.75	228	2	452	1	1513	2	1604
6	0.95	281	0	281	0.95	281	0	281	0.95	281	0	281	0.95	281	0	281	1	281	0	281
7	0.85	1841	0	1074	0.75	1124	2	1662	0.95	334	0	334	0.7	371	3	17	1	371	2	1662
8	0.95	381	0	381	0.95	381	0	381	0.95	381	0	381	0.95	381	0	381	1	381	0	381
9	0.95	415	0	415	0.95	415	0	415	0.95	415	0	415	0.95	415	0	415	1	415	0	415
10	0.85	656	0	600	0.75	309	2	151	0.85	656	0	600	0.75	1368	3	32	1	1368	3	151
11	0.95	472	0	472	0.95	472	0	472	0.95	472	0	472	0.95	472	0	472	1	472	0	472
12	0.95	1356	0	1356	0.75	1161	2	899	0.95	1356	0	1356	0.75	6	2	1827	1	1688	0	1356
13	0.95	53	0	53	0.95	53	0	53	0.95	53	0	53	0.95	53	0	53	1	53	0	53
14	0.85	573	0	185	0.85	169	1	1734	0.95	1615	0	1615	0.75	573	3	1281	1	573	1	1734
15	0.95	1861	0	1861	0.95	1861	0	1861	0.95	1861	0	1861	0.95	1229	0	1229	1	1861	0	1861
16	0.95	170	0	170	0.95	170	0	170	0.95	170	0	170	0.95	170	0	170	1	170	0	170
17	0.95	218	0	218	0.95	218	0	218	0.95	218	0	218	0.95	210	0	210	1	218	0	218
18	0.95	1693	0	1693	0.95	1693	0	1693	0.95	1693	0	1693	0.95	103	0	103	1	1693	0	1693
19	0.95	511	0	511	0.95	511	0	511	0.95	511	0	511	0.95	347	0	347	1	511	0	511
20	0.95	428	0	428	0.95	428	0	428	0.95	428	0	428	0.95	428	0	428	1	428	0	428
21	0.95	21	0	21	0.95	21	0	21	0.95	21	0	21	0.95	21	0	21	1	21	0	21
22	0.95	466	0	466	0.75	2	2	498	0.95	466	0	466	0.75	2	2	17	1	2	1	1267
23	0.95	325	0	325	0.95	325	0	325	0.95	325	0	325	0.95	325	0	325	1	325	0	325
24	0.95	1744	0	1744	0.95	1744	0	1744	0.95	1744	0	1744	0.75	1744	3	357	1	1744	3	1267
25	0.85	419	0	1744	0.85	419	0	1744	0.95	419	0	419	0.85	244	0	1744	1	627	0	1744
26	0.95	282	0	282	0.95	282	0	282	0.95	282	0	282	0.85	182	1	1770	1	182	0	282
27	0.95	277	0	277	0.95	277	0	277	0.95	277	0	277	0.95	222	0	222	1	277	0	277
28	0.85	394	1	1325	0.85	394	1	1325	0.95	5	0	5	0.75	5	2	378	1	5	2	1325
29	0.95	126	0	126	0.75	392	2	907	0.95	126	0	126	0.75	126	2	307	1	126	2	907
30	0.95	795	0	795	0.95	795	0	795	0.95	795	0	795	0.95	494	0	494	1	795	0	795
31	0.95	150	0	150	0.85	150	1	980	0.95	150	0	150	0.75	150	2	192	1	150	1	980
32	0.85	344	0	275	0.75	1384	2	1219	0.85	344	0	275	0.7	1384	3	1503	1	1384	2	1219
33	0.85	705	0	1115	0.75	467	2	1219	0.85	467	0	652	0.75	421	2	16	1	521	2	1035
34	0.95	1186	0	1186	0.95	1186	0	1186	0.95	1186	0	1186	0.75	1186	2	572	1	444	1	777
35	0.85	600	0	360	0.75	600	2	86	0.85	600	0	360	0.75	600	2	86	1	600	2	86
36	0.95	385	0	385	0.75	385	2	1775	0.95	385	0	385	0.75	385	2	1775	1	385	1	1056
37	0.95	1074	0	1074	0.95	1074	0	1074	0.95	1074	0	1074	0.95	1074	0	1074	1	1074	0	1074
38	0.85	485	0	515	0.75	485	2	498	0.95	195	0	195	0.75	652	2	164	1	195	2	1219
39	0.95	622	0	622	0.75	207	2	539	0.95	622	0	622	0.75	207	2	539	1	207	2	539
40	0.95	33	0	33	0.75	33	2	443	0.95	33	0	33	0.75	33	2	443	1	33	1	311
41	0.95	946	0	946	0.85	946	1	1348	0.95	946	0	946	0.75	110	2	373	1	110	1	1348
42	0.75	1816	2	341	0.75	1816	2	341	0.95	1284	0	1284	0.7	1816	3	798	1	155	2	341
43	0.95	1264	0	1264	0.85	1264	1	595	0.95	1264	0	1264	0.85	185	1	812	1	185	1	595
44	0.95	1194	0	1194	0.95	1194	0	1194	0.95	1194	0	1194	0.75	47	2	1736	1	47	1	1414
45	0.95	669	0	669	0.75	480	2	66	0.95	669	0	669	0.75	480	2	66	1	480	3	1836
46	0.95	343	0	343	0.75	445	2	574	0.95	343	0	343	0.75	343	2	253	1	343	2	574
47	0.95	37	0	37	0.75	37	2	1844	0.95	37	0	37	0.75	376	3	1844	1	35	1	149
48	0.95	491	0	491	0.95	491	0	491	0.95	491	0	491	0.85	14	1	1575	1	491	0	491
49	0.95	935	0	935	0.75	1260	2	1590	0.95	935	0	935	0.75	935	2	936	1	935	1	1434

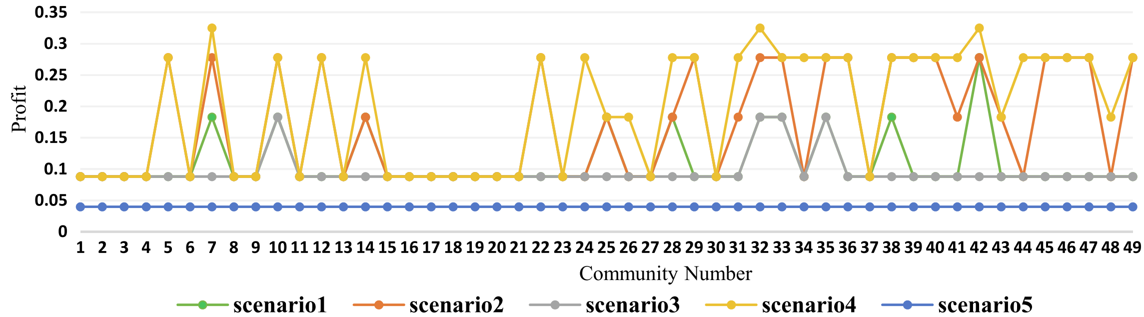

Fig. 11. The value of the profit objective function based on different scenarios.

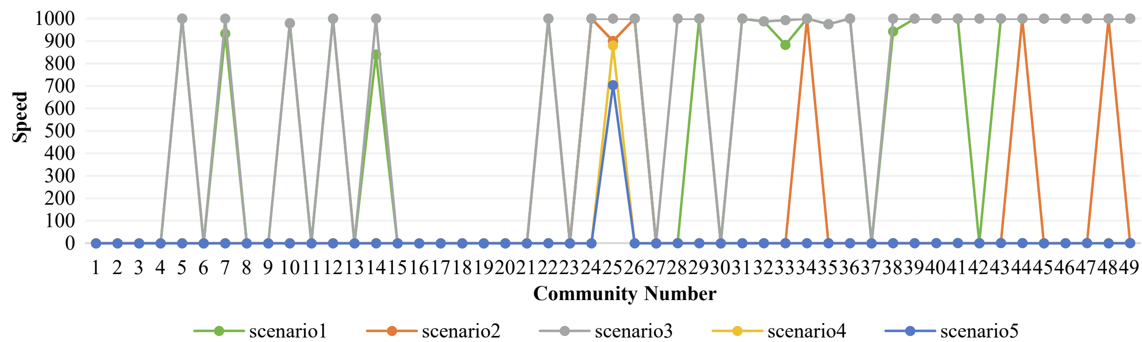

Fig. 12. The value of the second objective function based on different scenarios.

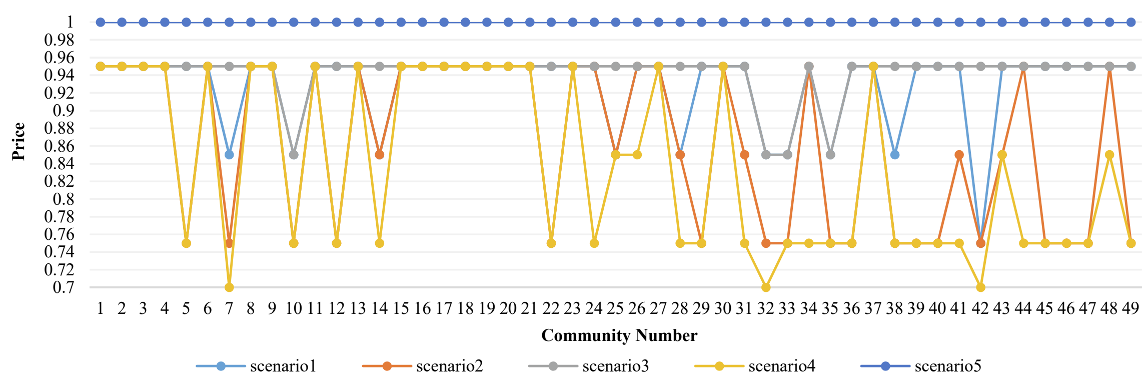

Fig. 13. The optimum values of the prices for different scenarios in each community.

tolerant scenario, such as Scenario 4). Accordingly, in Scenarios 4 and 5, 50 % and 25 % of the shipping orders are allocated to drivers with a distance of 2 and 3 from the leaders, respectively. On the other hand, companies that are novices and reluctant to extend the allocation time are more willing to allocate freight orders to the nearest drivers, that is, leaders or drivers at a distance of 1 from the community leaders (risk-averse scenario). Accordingly, in Scenarios 3 and 1, 100 % and 96 % of the shipping orders, respectively, are allocated to community leaders.

Fig. 15 shows the *VIKOR* index values for leaders and followers with distances of 1, 2, and 3 from the community leaders in each scenario. The average *VIKOR* value for Scenario 4 (0.6) is the worst (maximum) value compared with those of other scenarios. In this scenario, the weight value of 1 is considered for the company's profit function, which shows a 100 % focus on the profit function. Thus, most shipping orders are allocated to drivers who are at a distance of 2 or 3 from the community leaders. Therefore, we conclude that as shipping orders are allocated to the depths of the community (*i.e.*, followers at a distance of 2 and 3 from their community leaders), the experience and the communication of drivers decrease, which negatively affects the value of these followers' *VIKOR* index. In contrast, in Scenario 3, when more weight is considered for the third objective function, the *VIKOR* index has its best value because all shipping orders are allocated to community leaders and these leaders have the highest level of communication and experience in their communities.

According to this figure, as we move from community leaders to the depths of the community, the level of driver competency decreases. In all scenarios, community leaders have the lowest value in the *VIKOR* index. In other words, these leaders are the most suitable drivers for shipping orders. More distance from community leaders also results in a worse value in the *VIKOR* index because these drivers have lower communication levels and less work experience in freight transportation.

5.4. Managerial insights

Based on the above results, Table 10 shows two scenarios that are suitable for companies to allocate shipping orders to drivers based on three factors "cost", "speed" and "Risk".

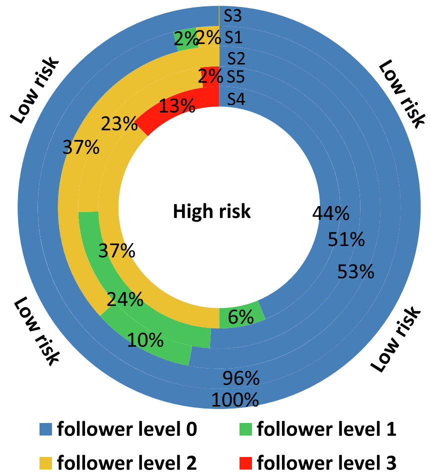

Fig. 14. The combination of selected drivers based on different scenarios (S_1, S_2, S_3, S_4, and S_5).

Based on the table, two scenarios can be derived as follows:

- **"Depth" of the community:**

By selecting this scenario, the company seeks to allocate shipping orders to drivers with the lowest possible cost. So, the optimisation model allocates the orders to drivers in the depth of communities, who are novices and are willing to accept the orders at a lower cost, due to their low experience level. These drivers also have little communication experience, which makes it less possibility to diffuse the shipping orders news to others. So, the allocation speed and the risk factors are at their worst value. Indeed, most well-known companies which have a large market share tend to choose the "depth" scenario.

- **"Level" of the community:**

In this scenario, the company seeks to allocate the shipping orders to drivers in the shortest possible time. Therefore, the speed and the risk factors are the most important for the company. By selecting this scenario, the optimisation model allocates the orders to community leaders or drivers at community level 1. Also, most novice companies tend to choose the "level" scenario.

Table 11 shows the results of the profit, speed and risk objective functions and also the selected drivers' information, in each case. In this table, the first row (the case #1) was considered as the base case, which results from solving the model with scenario 3 of Table 8. In this case, because of the great weight of the speed objective function, 100 % of drivers were selected from community leaders. Hence, the profit objective function is at its worst value (0.096). Based on the case #1, two different value types of the objective functions were extracted which are shown in "value" columns. So, the total values of the profit, the speed and the risk functions can be calculated, in each case.

Based on the information from Table 11, an analysis of changes in the total values of the objective functions is shown in Table 12.

Based on Table 12, by increasing 15 percentages in the profit objective function, the dispersion of the selected leader drivers was reduced by 6 %. As a result, drivers in levels 1 and 2 were selected for 3 communities. Therefore, the speed objective function is reduced by 7 % and the risk of losing customers is increased by 23 %. With a 50 % increase in the profit function, the dispersion of drivers in levels 1 and 2 increases by 30 %. Therefore, the freight allocation speed is decreased by 30 % and the risk objective function is increased by 41 %. Also, by increasing 75 % in the profit function, more than 40 % of drivers were selected in levels 1, 2 and 3. As a result, the allocation speed is reduced by 47 % and the risk of losing customers is increased by 51 %. Finally, with a 100 % increase in the profit function, more than 70 % of drivers were selected in levels 1, 2, and 3, and only 30 % of drivers included community leaders. As a result, the freight allocation speed decreases by 65 % and the risk of losing customers is increased by 57 percentages.

6. Conclusion

In this study, a multi-objective optimisation model for the TSP system is developed. In addition to considering the profitability of a company, the model also addresses the issue of allocating freight orders to the most suitable drivers in the shortest possible time.

Using the information diffusion ability of drivers by considering the social connections among them and modelling these communications in the context of the drivers' collaboration network concept are the key problems addressed in this paper. Considering this ability makes it possible to control and manage the diffusion of shipping order news among the drivers in the network. It means that a company can diffuse the shipping order information among certain drivers of the network, based on its policies (*i.e.,* making more profit, increasing the speed of freight allocation, or reducing the risk of losing customers).

The OCDEML algorithm is used to identify communities in the drivers' collaboration network. Another innovation of the multi-objective optimisation model is that the shipping order news is only diffused by the community leaders. One of the reasons for using the OCDEML algorithm is its ability to identify community leaders. By solving this algorithm, in addition to discovering the drivers' communities in the network, community leaders who can diffuse the shipping order news within the communities are identified.

The following results have been obtained by applying the multi-objective optimisation model:

- Well-known companies are more risk-tolerant because of their reputation, and they also tend to allocate shipping orders to drivers

Table 10
The scenarios in allocating orders to drivers.

Speed	Max min	Cost Min Depth	Max Level	min Max	Risk

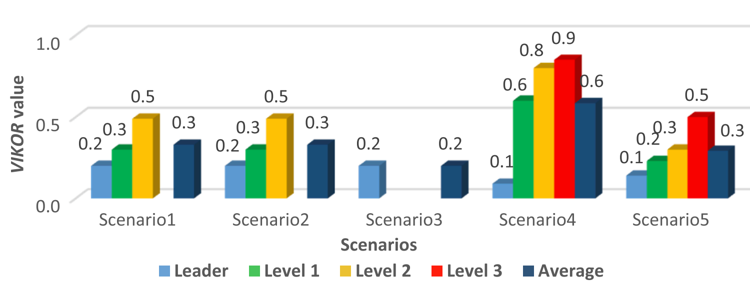

Fig. 15. Information of the *VIKOR* index.

Table 11
The objective functions results and the selected drivers in different cases.

Case	Selected drivers' features				Profit		Speed		Risk	
	Leader	Level 1	Level 2	Level 3	value	total value	value	total value	value	total value
1	45	0	0	0	0.088	0.096	1000	999	0.41	0.411
	4	0	0	0	0.183		983		0.42	
2	39	0	0	0	0.088	0.111	1000	931	0.49	0.506
	7	1	0	0	0.183		827		0.5	
	0	1	1	0	0.278		0.6		0.84	
3	25	0	0	0	0.088	0.144	1000	700	0.51	0.581
	10	4	5	0	0.183		490		0.63	
	0	1	4	0	0.278		0.5		0.75	
4	25	0	0	0	0.088	0.167	1000	532	0.53	0.619
	3	4	0	0	0.183		150		0.62	
	0	5	11	1	0.278		0.4		0.75	
5	13	7	0	0	0.088	0.192	800	345	0.44	0.646
	1	3	0	0	0.183		220		0.59	
	0	3	18	4	0.278		0.2		0.82	

Table 12
Analysing the behaviour of the objective functions.

Case	Objective functions			Selected drivers' features			
	Profit	Speed	Risk	Leader	Level 1	Level 2	Level 3
1	0 %	0 %	0 %	49	0	0	0
2	15 %	−7%	23 %	46	2	1	0
3	50 %	−30 %	41 %	35	5	9	0
4	75 %	−47 %	51 %	28	9	11	1
5	100 %	−65 %	57 %	14	13	18	4

in the depth of communities. These drivers accept shipping orders at lower wages due to their lower levels of communication and experience compared with those of other drivers, which ultimately leads to more profits for the companies.

- Novice companies that have fewer customers are reluctant to accept the high risk of prolonging the time to allocate orders and prefer to select drivers for their orders in the shortest possible time. Accordingly, either the community leaders or the drivers close to the community leaders are selected for the shipping orders. Due to the high levels of communication and experience of these drivers, they accept shipping orders at higher wages. As a result, the companies' profits are reduced, but their risk of losing customers is decreased as well.
- Based on the results obtained from the third objective function, as we move from community leaders to the depths of the communities, the drivers' suitability in accepting orders allocated to them decreases. Community leaders are recognised as influential people in the drivers' collaboration network due to their high levels of communication and experience. The deeper we go into the community (*i.e.,* drivers with distances of 2 and 3), the drivers have lower levels of communication and work experience, which affect their adequacy and competency.

The results of the model show the real behaviour of the TSP system. According to the results, if we define the company's profit in both short and long terms, the additional managerial insights obtained are as follows:

- Short-term profitability: For short-term profitability, especially well-established shipping companies can assign new shipping orders by searching deeper into the driver's communities for those who expect lower wages.
- Long-term profitability: Shipping companies, especially start-ups, are better off delivering freights to first-tier drivers for higher wages. In this way, they reduce the allocation time, and the freight is also allocated to an experienced driver. Therefore, two key factors in enhancing the company's reputation and thus retaining the customer for future orders are managed in this way.

CRediT authorship contribution statement

Hamed Kalantari: Conceptualization, Methodology, Software, Validation, Writing – review & editing, Project administration, Funding acquisition. **Aghdas Badiee:** Data curation, Methodology, Investigation, Formal analysis, Validation, Writing - original draft, Writing - review & editing. **Zahrasadat Tabaie:** Methodology, Visualization. **Mohammad Moshtari:** Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data file has been attached in files.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cie.2023.109005.

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