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A Stochastic Programming Model to Mitigate Disruption Effects on the Drug Distribution System Under an Autonomous Vehicle Fleet

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ABSTRACT

One of the most important problems of supply chain management is distribution management. The fleet composition and size play a significant role in reducing distribution costs. Recently, infectious diseases such as the COVID-19 pandemic have affected human resources, leading to the employment of autonomous vehicles (AVs) getting more attention. This paper proposes a stochastic programming model for the fleet size and mixed vehicle routing problem (FSMVRP), including autonomous and conventional vehicles (CVs) under human resource disruption. An accelerated version of the Progressive Hedging Algorithm (PHA) is applied to solve that. According to numerical results, the obtained value of the stochastic solution (VSS) suggest the model could decrease the fleet cost by about 11 percent on average. Analysis of the expected value of perfect information (EVPI) shows that using the stochastic programming approach for fleet management could minimize the total cost of the fleet by 22%, on average. In addition, the sensitivity analysis shows that using AVs under infectious disease disruption is advisable to improve performance.

Keywords: *autonomous vehicles, COVID-19 pandemic, stochastic programming model, supply chain management*

1. INTRODUCTION

In the vehicle routing problem (VRP), the decisions are made primarily at the operational and tactical levels. However, deliberating the effects of strategic decision levels on the lower levels is undeniable. Therefore, vehicle routing decisions often combine with other strategic or tactical decision levels and a longer horizon (Crainic, 2003). One of the strategic level decisions is the fleet size and composition, known as the fleet size and mix vehicle routing problem (FSMVRP) in the literature. This problem obtains the best fleet composition owing to the characteristics of each vehicle, such as loading capacity, applied technologies, fixed and operational costs, and the properties of demands, such as the demand volume, order period, and number of customers. FSMVRP was first introduced by Golden *et al.* (1984) as a variation of the classic VRP and, afterward, came to the attention of researchers in the VRP literature (Golden *et al.*, 1984).

In another categorization, there are two types of problems regarding the number of vehicles in the fleet: the FSMVRP, as mentioned earlier, and the heterogeneous fixed fleet vehicle routing problem (HFVRP). In the FSMVRP, the number of each type of vehicle is unlimited, while in the HFVRP, this assumption is considered bounded (Vidal *et al.*, 2020). Indeed, in the HFVRP, only the type of vehicle and routing decisions are determined. Based on the wide range of studies in the HFVRP, considering the period time and deterministic demand are common in modeling, though, this applies to the problems in which the fleet is pre-equipped or the demand rate is constant over a long time. Researchers have recently considered multi-periodic or stochastic assumptions to fill the gap between the HFVRP and FSMVRP (Koç *et al.*, 2016). For instance, the researchers studied an FSMVRP with different daily demands assumptions and aimed to optimize the fleet composition to meet all customer demands (Pasha *et al.*, 2016).

On the other hand, considering necessary parameters as stochastic in optimization problems is advisable for adapting them to the real world. That is important at the strategic decision-making level, especially because long-term decisions must be made more accurately and realistically.

Another efficient factor in the logistics scope is the use of emerging technologies because of the competitiveness of this field. In recent years, leading logistics companies have planned to employ autonomous vehicles (AVs). On the other hand, since 2019, COVID-19 has affected transportation and led to changes in the behavior of logistics companies, public transportation, and people. Marra *et al.* (2022) studied public transportation during COVID-19 to investigate how the pandemic affected people's travel behavior (Marra *et al.*, 2022). This phenomenon has also caused irreparable losses for many businesses. One problem is the lack of human resources in businesses that cannot be done online, like logistics companies. Although there has been a driver shortage crisis in the logistics companies previously, it has increased with this epidemic. According to recent studies, this pandemic has accelerated the production of AVs (Toapanta *et al.*, 2021).

In recent years, the global spread of the COVID-19 pandemic has significantly disrupted various industries, including pharmaceutical distribution. The urgent need for efficient and safe delivery of medications to pharmacies and hospitals has highlighted the limitations of traditional delivery methods, particularly concerning driver shortages and unpredictable customer demand. This situation has underscored the necessity for innovative solutions to ensure the timely and secure distribution of essential medical supplies.

To address these challenges, this study proposes a model for an FSMVRP tailored to the distribution of COVID-19 medications. The model incorporates AVs equipped with multiple compartments, each dedicated to a specific customer. This compartmentalized approach ensures that each customer's order is handled separately, maintaining the integrity of the delivery process and adhering to safety protocols. By leveraging AVs, the model aims to mitigate risks associated with driver shortages and demand uncertainties, thereby enhancing the efficiency and reliability of pharmaceutical distribution during the pandemic.

The proposed FSMVRP model offers a novel approach to pharmaceutical distribution by integrating AVs with dedicated compartments for each customer. This strategy streamlines the delivery process and enhances efficiency by reducing the complexity associated with managing multiple product types within a single vehicle. By focusing on customer-specific compartments within AVs, the model addresses the unique challenges posed by the COVID-19 pandemic, paving the way for more resilient and efficient distribution systems in the pharmaceutical industry.

On the other hand, the problem addressed is based on a case study and focuses on purchase and transportation costs, including insurance, depreciation, pollution penalty, tax, maintenance, fuel consumption, and the driver cost of CVs. This paper focuses on determining the composition and size of the fleet, considering the limited availability of conventional vehicles due to the COVID-19 pandemic. To employ this developed model in other cases, the researchers can comprehensively consider multiple factors, such as service quality and environmental impacts in actual logistics and distribution decisions that need to be discussed. As well as the model's applicability to other industries, such as food distribution, express logistics, and delivery of groceries, is an important aspect that can be explored further. Given the impact of workforce shortages in various sectors, integrating autonomous vehicles into different supply chains could mitigate similar disruptions beyond healthcare logistics. Additionally, incorporating real-world data for model optimization is a crucial direction for future research, allowing for more accurate and practical decision-making.

The rest of the paper is structured as follows. Section 2 provides the literature review. The problem description is discussed in Section 3, and the mathematical model is presented in Section 4. Section 5 offers the solution approach. Section 6 deals with the computational study, including scenario generation, the necessity of considering uncertainty, and numerical results. Finally, the paper's conclusions and future research are provided in Section 7.

2. LITERATURE REVIEW

VRP is a classic problem in optimization research with extensive literature. Although VRP is one of the tactical or operational decisions based on the planning horizon, it could link to some decisions at the strategic level. In the VRP literature, some of these combined problems include the location-routing problem (LRP), inventory-routing problem (IRP), and FSMVRP, in which the routing and other decisions are taken simultaneously. Two methods have also been applied to estimate the routing costs in these problems: the continuous estimation method and the Monte Carlo simulation method. The approximation method was introduced by (Laporte & Dejax, 1989), in which the Voronoi diagram divided catchment areas into polygons. Monte Carlo scenario generation instead of the optimization problem was used for LRP (Klibi *et al.*, 2010).

In the LRP literature, there is a prevalent assumption that the transportation routes are fixed over a long time, and most studies have applied a single deterministic routing scenario (Vidal *et al.*, 2020). However, considering stochastic parameters for the routing section leads to a more realistic solution to this problem. A two-stage stochastic programming model for a location-allocation-routing problem was presented for the case of railway network maintenance (Tönissen & Arts, 2020). In their model, the stochastic parameter was used to determine which railway line needed maintenance services.

The IRP was introduced in 1983 at two operational and tactical decision levels (Bell *et al.*, 1983). The IRP literature uses the continuous approximation method for the routing costs (Baller *et al.*, 2019) and the different inventory policies studied, like maximum inventory level (Manousakis *et al.*, 2022).

Like the previous two problems, LRP and IRP, the decision levels of the FSMVRP are not the same because the size and composition of the fleet are at the strategic level, unlike the routing problem. In land transportation, the routing costs are studied based on the two methods in the FSMVRP: continuous approximation and considering the multi-period or stochastic routing problem. In this regard, a composition of the fleet problem for urban logistics was presented in (Franceschetti *et al.*, 2017). A continuous approximation model was developed for that, and it was solved by a branch and cut (B&C). An FSMVRP was studied by considering greenhouse gas emissions and traffic restrictions for big trucks in Los Angeles (Nourinejad &

Roorda, 2017). Then, they analyzed the switch from big trucks to smaller types. In this regard, a mathematical model was developed to efficiently integrate the mid-term planning of the fleet and daily routine, and a large neighborhood search (LNS) was present as the solution method (Kilby & Urli, 2016). The same problem is introduced in the following, considering the vehicle rental option over time planning as an efficient alternative for daily distribution processes in the fleet management segment (Bertoli *et al.*, 2020). The routing assumptions were time windows, multi-product, and multi-compartment vehicle constraints. Then, a column generation method and three different heuristics were employed to solve the model.

Some uncertain parameters in the VRP lead to its proximity to the real world and more accurate planning, known as stochastic vehicle routing problem (SVRP). In the VRP literature, the most common stochastic parameters belong to the demand volume (Bertsimas, 1992), (Laporte *et al.*, 2002) customer presence at the determined location (Gendreau *et al.*, 1995), and uncertain travel and service times (Errico *et al.*, 2018). The VRP with stochastic demand (VRPSD) has been studied since 1969 (Tillman, 1969). To model a VRPSD, the two-stage stochastic programming model could be applied, and some recourse actions are ordinarily planned to reduce or overcome uncertainties. Indeed, the first stage decisions are related to before visiting the customers and the revelation of demands, and the second stage decisions are made after meeting the customers.

On the other hand, two methods employed to model the SVRP included Stochastic Programming with Recourse (SPR) and Chance Constraint Programming (CCP). In the SPR, the recourse actions are planned to react to or overcome possible violations of constraints because some stochastic parameters may violate the related constraints. The SPR estimates the recourse action costs in the objective function. The CCP controls the constraint violations by defining the chance constraints and determining the tolerable probability of a violation incident. The SPRs and CCPs are not independent and can be employed in combination, too. For example, a study presented a two-stage stochastic programming model for the VRP in which the time windows and service time were uncertain (Errico *et al.*, 2016). The authors applied both SPR and CCP policies in this research. Before visiting the customer, the service time and demands are unsure in the first stage. Accordingly, an initial plan was drafted to serve the customers at the first stage. When the orders were identified after meeting the customers at the second stage, the initial plan was revised according to the recourse action policy.

In the literature, fleet composition decisions have already been made, and the demand has been constant for a long time. FSMVRP with multi-period and random distribution of the demands is a new subject that has been recently extended by (Pasha *et al.*, 2016), (Kilby & Urli, 2016), and (Bertoli *et al.*, 2020). Also, driver shortage is one of the risks that fleets have been dealing with during the COVID-19 pandemic. So, in this paper, an FSMVRP that considers stochastic demands has been studied for a distribution company in the drug industry. The origin of this uncertainty is the COVID-19 pandemic, which is regarded as a disruption risk in the logistic system. This disruption affects the demand volume and leads to a shortage of drivers. In this regard, employing AVs in the fleet is proposed to mitigate the lack of driver risk. A two-stage stochastic programming model has been developed for this problem and solved by a progressive hedging algorithm (PHA).

Table 1 Parameters used in the model.

Notation	Definition
I	Set of nodes, $I=\{0,1,\ldots,N\}$
I_1	Set of customer type 1, including drugstores, $I_1 \subseteq I$
I_2	Set of customer type 2, including hospitals and health centers, $I_2 \subseteq I$
Ξ	Set of scenarios
V	Set of vehicles
AV	Set of autonomous vehicles $AV \subseteq V$, $\lvert AV \rvert = y_{AV}$
CV	Set of conventional vehicles, $CV \subseteq V$, $\lvert CV \rvert = y_{CV}$
C	Set of compartments of the autonomous vehicles
$p(\xi)$	The unavailability percentage of drivers under scenario $\xi \in \Xi$
a_{ij}	1 if the path i to j is allowable for the AVs, 0 otherwise
$W_{c,v}$	The capacity of compartment c in vehicle v
Q_v	The capacity of vehicle v
d_{ij}	The distance from node i to j
s_v	The average speed of vehicle v
t_i	The service time at node i
$d_i(\xi)$	The demand of customer i under scenario $\xi \in \Xi$
f_{CV}	The purchase price of a CV
f_{AV}	The purchase price of an AV
b_v	The transportation cost of vehicle v
dr	The driver's wage per hour
β	The Ratio of the effect of disruption severity on driver shortage cost
π	The penalty per lost customer
l_{CV}	The lifespan of CV
l_{AV}	The lifespan of AV
r	The inflation rate
BD	The annual budget amount for investment

3. PROBLEM DESCRIPTION

This study aims to present an FSMVRP, including the AVs and CVs, considering an infectious disease like the COVID-19 pandemic as a disruption risk for human resources. Customers' numbers and geographic range are fixed, but their demands $d_i(\xi)$ are uncertain under the scenario ξ. The customers are divided into subsets based on the market volume, I_1 and I_2. Set I_1 comprises customers with small or medium order volumes without needing to be unloaded by drivers like the drugstores. Set I_2 includes the customers for whom the driver's presence is essential, such as hospitals and health centers. The origin of the uncertainty in demand is the stochastic patient referral to these centers during the COVID-19 pandemic, which requires that there be adequately associated drugs and health products. Due to the absence of the drivers in the AVs, they cannot be employed for set I_2. The AVs have several compartments with different capacities; each must be assigned to only one customer (Farahani *et al.*, 2023). On the other hand, this pandemic has led to driver shortages in the fleet. The number of available CVs for each scenario is determined by defining $p(\xi)$ as the unavailable drivers percentage in scenario ξ.

In this regard, we propose a two-stage stochastic programming model. The first stage is related to the fleet composition of the *AVs* and *CVs* before knowing the availability percentage of drivers and the customer demands. In the second stage, the routing decisions are made after identifying them. The *AVs* are employed to service the I_1 set to mitigate driver shortage risk. The optimal fleet composition is obtained according to different $p(\xi)$ and $d_i(\xi)$ per scenario. The parameters and the decision variables are displayed in Tables 1 and 2, respectively.

Table 2 Decision variables of the model.

Notation	Definition
y_{AV}	Number of *AVs* that were purchased at the first stage
y_{CV}	Number of *CVs* that were purchased at the first stage
$x_{ijv}(\xi) = \begin{cases} 1 \\ 0 \end{cases}$	If vehicle *v* travels from location *i* to *j* under scenario $\xi \in \Xi$ Otherwise
$z_{ijv}(\xi) = \begin{cases} 1 \\ 0 \end{cases}$	If the order of customer *i* is delivered by vehicle *v* in compartment *c* under scenario $\xi \in \Xi$ Otherwise
$u_{iv}(\xi)$	Position of customer *i* on the tour of vehicle *v* under scenario $\xi \in \Xi$

4. MATHEMATICAL MODEL

Let us display the annual purchase cost of vehicles regarding their lifespans by f' as follows:

$$f'_{CV} = \left(\frac{r(1+r)^{l_{CV}}}{(1+r)^{l_{CV}}-1}\right) f_{CV},\quad f'_{AV} = \left(\frac{r(1+r)^{l_{AV}}}{(1+r)^{l_{AV}}-1}\right) f_{AV}.$$

The first stage of the model, including fleet size and composition, is displayed in (1)-(3), and the routing decisions are written in (4)-(17).

$$\text{DEP } Min.\, f'_{CV}.y_{CV} + f'_{AV}.y_{AV} + E_\xi(Q(y,\xi)) \tag{1}$$

s. t.

$$f'_{CV}.y_{CV} + f'_{AV}.y_{AV} \le BD \tag{2}$$

$$y_{CV}, y_{AV} \in Z^+ \tag{3}$$

where:

$$Q(y,\xi) = \min\{\sum_{i\in I}\sum_{j\in I}\sum_{v\in V} b_v.d_{ij}.x_{ijv}(\xi) + \sum_i\sum_j\sum_{v\in CV} dr.(1 + \beta.p(\xi)).(t_j + \frac{d_{ij}}{s_v}).x_{ijv}(\xi)) + \pi(N - \sum_{\substack{i\in I\\ i\neq 0}}\sum_{\substack{j\in I\\ j\neq i}}\sum_{v\in V} x_{ijv}(\xi))\} \tag{4}$$

s. t.

$$\sum_{v\in CV}\sum_{j\in I} x_{0jv}(\xi) \le \lfloor y_{CV}(1-p(\xi))\rfloor, \forall \xi \in \Xi \tag{5}$$

$$\sum_{v\in AV}\sum_{j\in I} x_{0jv}(\xi) = y_{AV}, \forall \xi \in \Xi \tag{6}$$

$$\sum_{j\in I} x_{0jv}(\xi) \le 1, \forall j \in I, v \in V, \xi \in \Xi \tag{7}$$

$$x_{ijv}(\xi) = 0, \forall i \in I, j \in I_2, v \in AV, \xi \in \Xi \tag{8}$$

$$x_{ijv}(\xi) \le a_{ij}, \forall i,j \in I, v \in AV, \xi \in \Xi \tag{9}$$

$$\sum_{i\in I} x_{ijv}(\xi) = \sum_{i\in I} x_{jiv}(\xi), \forall j \in I, v \in V, \xi \in \Xi \tag{10}$$

$$\sum_{i\in I}\sum_{v} x_{ijv}(\xi) \le 1, \forall j \in I/\{0\}, \xi \in \Xi \tag{11}$$

$$u_{iv}(\xi) - u_{jv}(\xi) + N.x_{ijv}(\xi) \le N-1, \forall i \in I, j \in I/\{0\}, v \in V, \xi \in \Xi \tag{12}$$

$$\sum_{i\in I_1} d_i(\xi) z_{ivc}(\xi) \le \sum_{i\in I_1} w_{c,v} z_{ivc}(\xi), \forall v \in AV, c \in C, \xi \in \Xi \tag{13}$$

$$\sum_{j\in I} x_{ijv}(\xi) = \sum_{c\in C} z_{ivc}(\xi), \forall v \in AV, i \in I_1, \xi \in \Xi \tag{14}$$

$$\sum_{i\in I_1} z_{ivc}(\xi) \le 1, \forall v \in AV, c \in C, \xi \in \Xi \tag{15}$$

$$\sum_{i\in I}\sum_{\substack{j\in I\\ j\neq 0}} d_i(\xi) x_{ijv}(\xi) \le Q_v, \forall v \in CV, \xi \in \Xi \tag{16}$$

$$x_{ijv}(\xi),\ z_{ivc}(\xi) \in \{0,1\}, u_{iv}(\xi) \in \{0,\ldots,N\},\ \forall i,j \in I, v \in V, c \in C, \xi \in \Xi \tag{17}$$

The objective function (1) consists of two deterministic terms that calculate the total cost, including purchase costs of vehicles AVs and CVs and the expected value of the routing costs. Constraint (2) ensures the cost of purchasing two types of vehicles should not exceed the given annual investment budget at the first stage. Equations (3) show the first stage decision variables.

Function (4) includes three terms related to routing decisions. The first term calculates the overload cost dependent on the distance traveled per type of vehicle. According to the defined disruption, the driver's wage is directly affected by the severity of the disruption. This means that the more severe the disruption, the fewer drivers will be available, leading to an increase in the driver wage shown in the second term of (4). The last term is related to the lost customer cost, which the fleet cannot service because of the unavailability of CVs. Constraints (5) and (6) show the number of available CVs and AVs. To linearize (5), although the number of available CVs is $\lfloor y_{CV}(1-p(\xi))\rfloor$, the right hand can be replaced by $y_{CV}(1-p(\xi))$, because its left hand is an integer. Constraints (7) enforce that each vehicle only takes one tour and cannot return to the depot before finishing the tour. Constraints (8) prevent the allocating of AVs to the I_2 set. Constraints (9) guarantee AVs can only cross authorized paths equipped with their special infrastructure. Constraints (10) for each node and vehicle ensure the number of input arcs is precisely equal to the number of output arcs.

In the standard VRP models, the constraints (11) are shown as equality constraints. Still, some customers may not be visited because of the unavailability probability of CVs, so constraints (11) are unequal. Constraints (12) prevent the sub-tour formation by considering a variable u_{iv} as the location of i in the tour of the vehicle v. Constraints (13) imply the loading capacity constraints for every compartment of AVs. Constraints (14) guarantee that customer i is visited by an AV if their orders are in at least one compartment. Constraints (15) indicate that each compartment must be assigned to one customer. Constraints (16) are loading capacity constraints for conventional vehicles. In the last, equations (17) show the type and domains of the decision variables of the second stage.

5. THE SOLUTION METHOD

According to the proposed deterministic equivalent problem (DEP) model, by increasing the number of scenarios, $|\Xi|$, the problem dimension will increase, consequently, the computational time will be increased. In the literature, PHA is one of the popular solution methods for two-stage and multi-stage stochastic programming models. For example, PHA was employed to solve a multi-stage stochastic programming model (Khalilabadi *et al.*, 2020) and extended to two-stage stochastic programming (Bashiri *et al.*, 2021). PHA decomposes a stochastic problem into separated scenario-based subproblems and solves them independently. This method replicates the first-stage variables per scenario, and the non-anticipativity constraints are relaxed. Although PHA has been applied as an exact solution method for the models with continuous variables in the literature, there is no guarantee of convergence to the optimal solution in the case of stochastic integer programming models, and PHA is used as a heuristic. For instance, an innovative PHA is presented for a mixed-integer problem model (Watson & Woodruff, 2011). Accordingly, we use the PHA studied in (Watson & Woodruff, 2011) to solve our model.

Moreover, the applicability of PHA in large-scale stochastic logistics problems has been supported in previous studies. Santoso *et al.* (2005) proposed a two-stage stochastic programming framework for supply chain network design under demand and cost uncertainty, highlighting the advantages of decomposition-based approaches such as PHA. Similarly, Lium *et al.* (2009) examined the impact of demand variability in service network design using stochastic programming models, further confirming the importance of scenario-based solution methods. These studies provide a solid foundation for using PHA in complex logistics problems.

In addition, the PHA is particularly effective for two-stage stochastic programming problems due to its ability to manage scenario-based uncertainty while maintaining a decomposable structure (Rockafellar & Wets, 1991). Its iterative nature allows for the flexible handling of complex problems where the first-stage decisions (e.g., fleet sizing) must be optimized before observing scenario realizations in the second stage (e.g., routing and assignment). This structure makes PHA a robust and scalable tool for vehicle routing problems with uncertainty, especially in real-world applications.

5.1 Progressive Hedging Algorithm

To employ the PHA, the decision variables of the first stage must be replaced by scenario-based variables. Therefore, the first stage programming model changes to (18-20) and the related constraints (5-6) in the second stage to (22-23).

$$\text{PH: } Min.\, f'_{CV}y_{CV}(\xi)+f'_{AV}y_{AV}(\xi)+E_\xi(Q(y,\xi)) \quad (18)$$

s. t.

$$f'_{CV}y_{CV}(\xi)+f'_{AV}y_{AV}(\xi)\le BD \quad (19)$$

$$y_{CV}(\xi),\ y_{AV}(\xi)\in Z^+, \xi\in\Xi \quad (20)$$

$$Q(y,\xi)=\min\{\sum_{i\in I}\sum_{j\in I}\sum_{v\in V} b_v.d_{ij}.x_{ijv}(\xi) + \sum_i\sum_j\sum_{v\in CV} dr.(1+\beta.p(\xi)).(t_j+\frac{d_{ij}}{s_v}).x_{ijv}(\xi) + \pi(N-\sum_{\substack{i\in I\\ i\neq 0}}\sum_{\substack{j\in I\\ j\neq i}}\sum_{v\in V}x_{ijv}(\xi))\} \quad (21)$$

s. t.

$$\sum_{v\in CV}\sum_{j\in I} x_{0jv}(\xi)\le y_{CV}(1-p(\xi)), \forall\xi\in\Xi \quad (22)$$

$$\sum_{v\in AV}\sum_{j\in I} x_{0jv}(\xi)= y_{AV}, \forall\xi\in\Xi \quad (23)$$

(7-17)

To present the PHA method, let's define a simple two-stage stochastic problem as follows:

Minimize $f.y(\xi)+\frac{1}{|\Xi|}\sum_{\xi\in\Xi}c(\xi)x(\xi)$
Subject to: $(y(\xi),x(\xi))\in Q_\xi, \forall\xi\in\Xi$

where Q_ξ is a solution in which all constraints are satisfied for each scenario. The steps of PHA for this problem are described in Algorithm 1.

Algorithm 1: The progressive hedging for FSMVRP

Input ($r, \varepsilon, L_r, k_{max}$)
$k \leftarrow 0;$
For $\xi \in \Xi$ **do**
$y^{(k)}(\xi) \leftarrow \text{argmin}\{f.y + c(\xi)x(\xi) | (y, x(\xi)) \in Q_\xi\};$
$\bar{y}^{(k)} \leftarrow \frac{1}{|\Xi|}. \sum_{\xi \in \Xi} y^{(k)}(\xi)$;
$\rho^{(k)}(\xi) \leftarrow r(y^{(k)}(\xi) - \bar{y}^{(k)});$
condition← false;
while the condition is false, **do**
For $\xi \in \Xi$ **do**
$y^{(k+1)}(\xi) \leftarrow \{f.y + \rho^{(k)}(\xi)y + r\|y - \bar{y}^{(k)}\|^2 + c(\xi)x(\xi) | (y, x(\xi)) \in Q_\xi\};$
$\bar{y}^{(k+1)} \leftarrow \frac{1}{|\Xi|}. \sum_{\xi \in \Xi} y^{(k+1)}(\xi);$
$\rho^{(k+1)}(\xi) \leftarrow \rho^{(k)}(\xi) + r(y^{(k)}(\xi) - \bar{y}^{(k)});$
$g^{(k+1)} \leftarrow \frac{1}{|\Xi|}. \sum_{\xi \in \Xi} \|y^{(k+1)}(\xi) - \bar{y}^{(k+1)}\|;$
If $g^{(k+1)} \leq 2\varepsilon$
If $r > L_r$
$r \leftarrow r/2$
If $g^{(k+1)} < \varepsilon$ or $k = k_{max}$ **then**
condition← true;
else
$k \leftarrow k+1;$

According to PHA literature, the quality of the final result depends considerably on the defined value of *r* (Khalilabadi *et al.*, 2020). Although a smaller value of *r* leads to searching the space more thoroughly, CPU time will be noticeably larger. Therefore, establishing a balance between the quality of the solution and the CPU time plays an important role in this method. Generally, three approaches have been used in the studies: The constant value for all of the variables (Khalilabadi *et al.*, 2020), the reduction method in which the algorithm begins with a large *r* and then reduces that iteratively (Watson *et al.*, 2012), and a heuristic approach to select the *r* value (Watson & Woodruff, 2011).

This paper defines a dynamic parameter as the termination criteria controlled with a lower bound, namely *Lr*. This heuristic adjusts *r* so that it is not less than a certain limit and does not lead to a decrease in the algorithm's speed. If *g* was smaller than *2e*, *r* is halved, that lower bound *Lr* controls its value, and if *r* moved away from *e*, it was unchanged.

There are the quadratic penalty terms in the objective function of algorithm 1, and the model is nonlinear consequently. We have changed the integer decision variables to binary variables to linearize the model. For this purpose, we have used the static piecewise linearization functions presented in (Watson *et al.*, 2012). In this regard, the first stage decision variables, y_{cv}, and y_{AV}, are converted to $y_{cv,s}$, and $y_{AV,s}$ respectively, as follows:

$$y_v = \sum_{s=0}^{S} 2^s y_{v,s} \ , S = \left\lceil \frac{ln(y+1)}{ln2} - 1 \right\rceil \in \{0,1\}, v \in \{AV, CV\} \quad (24)$$

Then, y_v^2 in the quadratic term $\|y_v - \bar{y_v}^{(k)}\|^2$ is calculated as:

$$y_v^2 = \sum_{s=0}^{S} 2^{2s} y_{v,s}^2 + \sum_{s=0}^{S} \sum_{\substack{s'=0 \\ s' \neq s}}^{S} 2^{s+s'} y_{v,s} \cdot y_{v,s'} \quad (25)$$

Note that the binary variable $y^2_{v,s}$ equals $y_{v,s}$. To linearize the multiplied term $y_{v,s}$. $y_{v,s'}$, the binary variable $e_{v,s,s'}$ is replaced:

$$y_v^2 = \sum_{s=0}^{S} 2^{2s}. y_{v,s} + \sum_{s=0}^{S} \sum_{\substack{s'=0 \\ s' \neq s}}^{S} 2^{s+s'}. e_{v,s,s'} \quad (26)$$

$$e_{v,s,s'} \geq y_{v,s} + y_{v,s'} - 1 \quad (27)$$

$$e_{v,s,s'} \leq y_{v,s} \quad (28)$$

$$e_{v,s,s'} \leq y_{v,s'} \quad (29)$$

Therefore, adding (26-29) to the PH model could solve it as a linear programming model.

6. COMPUTATIONAL STUDY

This section studies some problem instances to validate the proposed model and solution method. PHA is implemented with GAMS/CPLEX on a personal computer with a Core i7 8550u 1.80GHz CPU and 12GB of RAM.

Table 3 Values of the parameters.

Notation	Values	References
N	10	-
$\|I_1\|$	6	-
$\|I_2\|$	4	-
$\|\Xi\|$	{5, 10, 15, 20, 30, 40, 50, 80, 100, 150}	-
$p(\xi)$	U{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6}	-
$W_{c,v}$	{30, 30, 30, 50, 50, 50}	-
Q_v	200	-
s_v	AV: 60 km/hr CV:80 km/hr	-
t_i	0.25 hr	-
$d_i(\xi)$	*N* (μ, σ), ∀ μ ~U [0, Qv], σ ~ (0.1+0.1*U [0, 1]) * μ	-
f_{CV}	\$12000	(Chen *et al.*, 2019)
f_{AV}	\$22000	(Chen *et al.*, 2019)
b_v	AV: 0.016 (\$/mile) CV: 0.04 (\$/mile)	-
dr	13 (\$/hr)	-
β	1/3	-
l_{CV}	10 year	-
l_{AV}	15 year	-
r	0.03	-
BD	\$5000/year	-

In this study, customers' demands and drivers' unavailability percentages are stochastic parameters. The scenario generation method is described in the following. The demand of customer i is a normal probability distribution function with a mean value chosen randomly from the range [0, Qv]. Then, they are rounded to the nearest integer (Mendoza *et al.*, 2010). The values of the problem parameters are given in Table 3.

6.1 Scenario Generation

In this paper, we propose a stochastic programming model for an FSMVRP. To generate the scenarios for the stochastic demands, we used the coronavirus data from https://ourworldindata.org/coronavirus. Then, based on the daily new cases smoothed from November 2020 until December 2020, one wave of the pandemic in Iran, EasyFit Software approximately fits the normal distribution according to Fig.1. Note the normal distribution has been estimated for one wave of this pandemic since the driver shortage in every wave is more probable. Therefore, we applied the normal distribution of $N(\mu, \sigma)$ for the demands in which μ and σ parameters are presented in Table 3. According to Fig 1, the Normal distribution is the 10th distribution among 60 different statistical distributions.

Anderson-Darling					
Sample Size			73		
Statistic			1.891		
Rank			10		
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.375	1.929	2.502	3.290	3.907
Reject?	**Yes**	No	No	No	No

Figure 1 The goodness of fit Anderson-Darling test for the smoothed new cases of COVID-19 in Iran.

6.2 The Necessity of Considering Uncertainty

In stochastic programming studies, two important metrics should be investigated to measure the value of a stochastic model compared with a deterministic one. Their definitions and the required equations or models are presented below.

- Wait and See (WS): This problem concerns decisions based on the perfect information. The WS value is the optimal objective value of (30) with constraints (2-17).

$$\text{WS: min.} E_\xi(f'_{CV} y_{CV}(\xi) + f'_{AV} y_{AV}(\xi)) + E_\xi(Q(y,\xi)) \quad \text{s.t: } (2)-(17) \tag{30}$$

- Expectation of the Expected Value (EEV): The EEV model is displayed in the following. $\overline{y}_{CV}.\overline{y}_{CV}$ and $\overline{y}_{AV}.\overline{y}_{AV}$ the fixed parameters in (31) are obtained from solving a deterministic model by considering the mean values of stochastic parameters.

$$\text{EEV: } \quad \text{min.} f'_{CV}\overline{y}_{CV} + f'_{AV}\overline{y}_{AV} + E_\xi(Q(y,\xi)) \quad \text{s.t: } (2)-(17) \tag{31}$$

- Expected Value of Perfect Information (EVPI): This metric measures the maximum cost a decision-maker will pay to obtain excellent information about the future, calculated as the difference between the objective value of the PH model and WS according to equation (32).

$$EVPI = \frac{OF_{PH} - OF_{WS}}{OF_{WS}} \tag{32}$$

- Value of Stochastic Solution (VSS): Overlooking the stochastic parameters in the model might lead to a considerable loss. This metric determines the loss by calculating the difference between the EEV and the objective value of the PH as follows:

$$VSS = \frac{OF_{EEV} - OF_{PH}}{OF_{PH}} \tag{33}$$

6.3 Numerical Results

In this section, the performance of the PHA and the value of the proposed stochastic programming model according to the four metrics are studied.

Table 4 Comparison between DEP and PHA.

#Scenarios	DEP					PHA					Gap%
	OF	Investment	AV	CV	time	OF	Investment	AV	CV	Time	
5	6332.812	5500	1	4	3 min 32s	6489.338	5500	1	4	1 min 10s	2.50%
10	6036	4500	1	3	7000s	5462.22	3000	0	3	7min 41s	-9.50%
15	4850	4500	1	3	7000s	4382.56	3500	1	2	4min 38	-9.60%
20	-	-	-	-	-	4190.45	3000	0	3	7min35s	-
30	-	-	-	-	-	6320.64	3500	1	2	16 min 50s	-
40	-	-	-	-	-	6010.344	3500	1	2	14min 8 s	-
50	-	-	-	-	-	6590.472	4500	1	3	11 min 13s	-
80	-	-	-	-	-	6473.022	4500	1	3	30 min 44 s	-
100	-	-	-	-	-	6331.195	4500	1	3	28 min 6 s	-
150	-	-	-	-	-	6292.987	4500	1	3	42min47s	-

The presented PH and DEP models have been executed for different scenario sizes with CPLEX software, and the results are reported in Table 4. According to Table 4, although DEP obtains a better solution in less time for five scenarios, it cannot find the optimal solution for ten and fifteen scenarios, even in the 7000 seconds. Indeed, by increasing the scenario sizes, the PH algorithm is better than DEP in terms of the objective function and runtime. It is worth noting that, as indicated in the literature, this problem (FMSVRP) has been studied considering the multi-period and random distribution of the demands. Still, it has not been studied in a stochastic environment. In contrast, a two-stage stochastic programming model was developed in our manuscript. Moreover, considering the COVID-19 pandemic and the potential unavailability of vehicles, which could lead to customer loss, constitutes one of the key innovations of the proposed model. Therefore, due to the uniqueness of the modeling approach, the developed solution methods cannot be directly compared with those used in this paper.

Table 5 presents four metrics: WS, EEV, EVPI, and VSS. Fig. 2 and Fig. 3 illustrate the related charts. According to Fig. 2, although by increasing the number of scenarios to 20, PH is reduced and then increased to 50, the changes are invisible after 50 scenarios. So, it can be concluded that considering 50 scenarios is the proper way to make the decision.

According to Fig. 3, by increasing the number of scenarios, EVPI and VSS are increased. However, from scenario 50, the upward trend is reduced for VSS. Consequently, the loss of ignoring stochastic parameters after the number of scenarios 50 is slower in the model. However, according to EVPI, the decision-maker is still ready to pay more to earn the perfect information. Therefore, as a suggestion, a proportion of EVPI can be spent to motivate the customers to declare their exact demands.

Table 5 WS, EEV, EVPI, and VSS indices for the problem.

#Scenarios	WS	PH	EEV	EVPI	VSS
5	5833.33	6489.338	6593.74	11.2%	1.6%
10	4568.31	5462.22	5736.664	19.6%	5.0%
15	3482.681	4382.56	4850.392	25.8%	10.7%
20	3355.042	4190.45	4768.967	24.9%	13.8%
30	5345.011	6320.64	6923.57	18.3%	9.5%
40	4881.982	6010.344	6682.436	23.1%	11.2%
50	5395.078	6590.472	7564.579	22.2%	14.8%
80	5165.478	6473.022	7483.113	25.3%	15.6%
100	5047.197	6331.195	7283.31	25.4%	15.0%
150	5026.733	6292.987	7218.984	25.2%	14.7%
Average	4810.0842	5854.3228	6510.5755	22.1%	11.2%

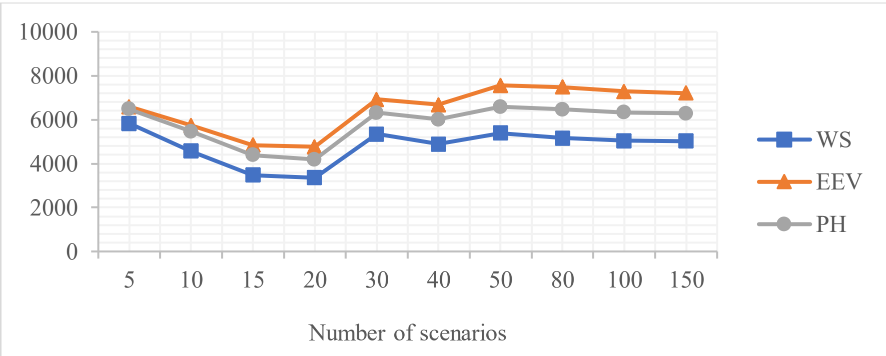

Figure 2 Comparison of WS, PH, and EEV for different numbers of scenarios.

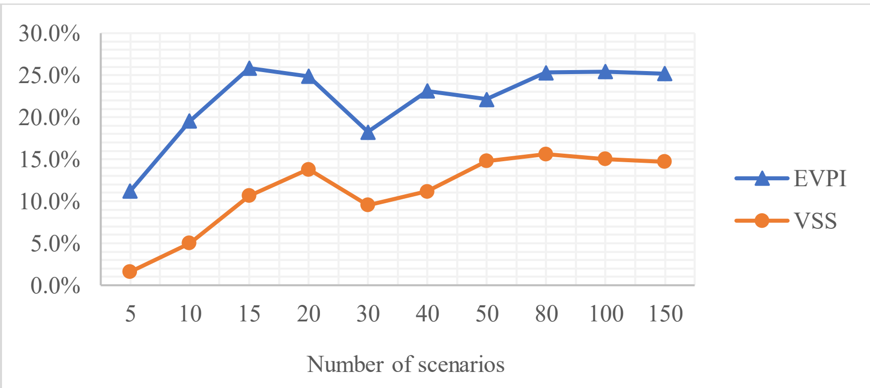

Figure 3 Comparison of EVPI and VSS for different numbers of scenarios.

The number of purchased vehicles by the fleet is fixed in more than 50 scenarios, as shown in Fig. 4. On the other hand, for the solved instance of the case study, the optimal composition of the fleet is three CVs and one AV. Therefore, it can be concluded that although AVs have a higher investment cost than CVs, using them under infectious disease disruption is advisable.

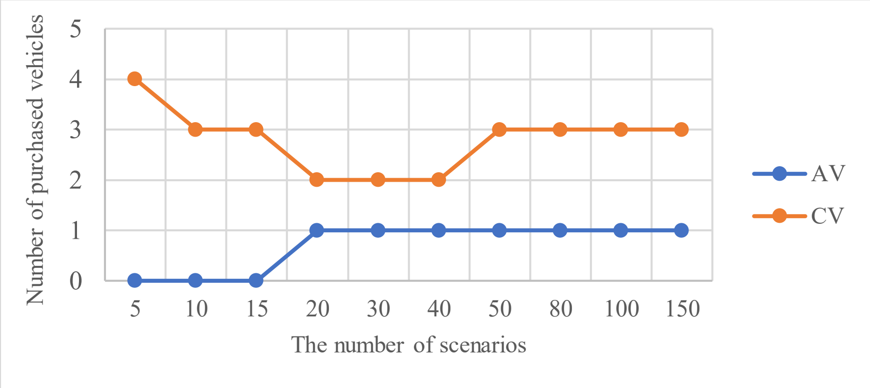

Figure 4 Composition of the fleet for a different number of scenarios.

7. CONCLUSION

This study developed a stochastic FSMVRP model for the fleet, including AVs and CVs, considering an infectious disease as a disruption. This problem description was based on the world experience gained during the COVID-19 pandemic. One of the main problems in this situation is the shortage of human resources for the jobs in which telework is impossible. This problem in the distribution process of logistics companies is more prominent. As mentioned in the introduction section, the reports indicate that the movement towards the usage of AVs has accelerated during the COVID-19 pandemic. On the other hand, in the drug industry, this disruption led to uncertainty about the demands of COVID-19 drugs. Hence, the main contribution of this study was investigating an FSMVRP under the infectious disease disruption that led to uncertainty of demand. The proposed model is usable for the investment step of different fleet sizes. Then, the progressive hedging algorithm was employed to solve the model. The numerical results showed that PHA achieved better solutions in much less time than the DEP model when the number of scenarios increased.

The efficiency of the stochastic model was studied according to the VSS and EVPI metrics. The numerical results indicated that using the proposed stochastic programming model could decrease the system's total cost based on the VSS metric. The EVPI metric showed that using a stochastic programming approach for fleet management could reduce the total fleet cost. The sensitivity analysis displayed that using AVs was proposed to mitigate the driver shortage risk during the COVID-19 pandemic. Future research could be conducted to develop a similar FSMVRP model using an approximation method to estimate the VRP costs. In addition, the composition of VRPSD with FSMVRP as a multi-stage stochastic programming problem could be of interest.

Despite the promising results and the novelty of the proposed two-stage stochastic model, this study has limitations that should be acknowledged. Due to the unique formulation and real-world context of the problem, direct quantitative comparisons with existing models were not feasible. Moreover, most prior approaches do not address human resource disruptions within the vehicle routing context, which limits the availability of appropriate benchmarks. In addition, the model was applied to a single case study, which may affect the generalizability of the findings. Future research could extend this work by using the model to multiple scenarios, developing comparative frameworks, and exploring additional dimensions of uncertainty and disruption.

CONFLICTS OF 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 STATEMENTS

Data will be made available on request.

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