A Hybrid Robust-Stochastic Optimization Approach for the Noise Pollution Routing Problem with a Heterogeneous Vehicle Fleet

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Abstract. One of the most important goals of green logistics is to reduce the destructive side effects of freight transportation which can lead to several types of health risks. The pollution routing problem (PRP) is an extension of the vehicle routing problem (VRP) which considers greenhouse gas emission in addition to the travel time, cost, and delivery constraints. Another environmental impact of vehicles, especially in urban areas is noise emission which is ignored in optimization PRP researches. This form of pollution endangers physical well-being by causing annoyance, hearing loss, heart disease, mental issues for children, and sleep disorders. In this paper, using noise emission mathematical equations, we aim to reduce noise and exhaust gas emission in VRP with a heterogeneous vehicle fleet and respect to budget, and time window constraints. Moreover, a new hybrid robust-stochastic optimization approach is developed which can address interval uncertainty of parameters in each individual uncertainty scenario. This model suggests a range of solutions that can be selected according to decision maker conservatism level and preferences. To examine the performance of the model, a real-world data sets from PRPLIB instances are adopted. The results approve the possibility of finding a sustainable solution for VRP which takes into account various aspects including fuel consumption, and noise emission simultaneously.

Keywords: Pollution routing problem · Noise emission · Robust optimization · Uncertainty · Vehicle routing problem

1 Introduction

The pernicious effects of transportation on the environment and human should not be ignored under the shadow of ease that it brings to life. The negative effects such as noise and greenhouse gas emission, resource depletion, acidification, and toxic effects

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on ecosystems are all caused by transportation [1]. Since introducing the Vehicle Routing Problem (VRP), many kinds of research have been conducted to minimize the destructive effects of transportation by selecting between different vehicle routes based on customer demands. In the VRP an attempt is made to minimize the total travelled distance by all vehicles. More sophisticated models were introduced based on VRP, taking into account fuel consumption [2].

Germany target to drop down greenhouse gas emissions (GHG) by 40% until 2020, by 55% by 2030 and up to 95% in 2050 [3]. It shows that green logistic is a vital research topic to meet this ambitious goal. Green Vehicle Routing Problem was also used by [4] and led to an improvement called Pollution Routing Problem (PRP) [2] in which a time window is used for VRP (VRPTW).

Ignoring uncertainty in operations research models may lead to infeasibility in realization [5]. In other words, a presumed optimal solution can be violated in practice because of interruptions in the input data. A different source of uncertainty is known in VRP, including travel time, demand, and customers.

In this paper a new PRP-based model is introduced, in which, for the first time the effect of noise is taken into account. Considering the deleterious effects of noise pollution on the environment and human mental and physical well-being, it is absolutely vital to include it to the Pollution Routing Problem. This model is called the Hybrid Robust-stochastic Noise Pollution Routing Problem (HRNPRP). Including noise emission factor in optimization process leads to more comprehensive and robust results under uncertainty which work as a preventive factor improving the health related quality of life by elimination of the detrimental effects of noise exposure such as annoyance, hearing loss, cardiovascular disease, sleep disturbance, nervousness, etc. The main contributions of this paper are as follow:

- A new hybrid Robust-stochastic approach to manage uncertainty in VRP
- Including noise emission in the PRP
- Investment optimization in PRP
- Considering noise-sensitive areas such as hospitals and residential areas to find optimal routs

2 Literature Review

The existing literature on PRP and noise modeling in transportation are reviewed in this section. Due to the importance of the problem, many researchers are focused on this topic and similar such as green logistics. To find out more about operations research investigations on green logistics and related works, readers are referred to the most recent review paper on this subject [6].

Green vehicle routing problem is an extension to VRP by taking into account CO_2 emission [7]. PRP is based on GVRP which introduced by [2]. PRP is a time windowed VRP aiming at minimizing fuel consumption, greenhouse gas emission, and cost in a multi-destination routing service for customers [8]. PRP is a NP-hard problem; therefor, some studies conducted heuristic, and meta-heuristic to solve this problem in a reasonable time.

Very recent works on this topic are presented [9]. In this article a novel energy model is developed to consider account speed, acceleration, deceleration, load cargo and gradients. In this heterogeneous model, light to heavy-duty vehicles as well as electric ones are included.

So far few researches have been conducted with the focus on the uncertainty of problem. In [8], a robust optimization approach is adopted for a homogenous PRP model with time-window to tackle the demand uncertainty.

There are many noise emission models which work mostly based on the same concept; however, they have not included in routing optimization models. Depending on the model, the impact of various parameters, including frequency, acceleration, and speed, will be investigated. Moreover, there are some compensation factors depending on the category of vehicles, road conditions, etc. A comprehensive review of different noise emission models can be found in [10].

Reviewing related literature, indicates that many researches have been carried out in PRP field and tremendous improvements have been achieved specially in recent years. Including the effect of noise pollution as a serious problem improves the model significantly. Moreover, just a few papers can be found which address the uncertainty of the PRP models to find more practical solution in realization and hybrid robust-stochastic approaches are totally ignored. Finally, budget constraint to select heterogeneous vehicle fleet is only considered in few papers which considered types of vehicles.

3 Model Formulation

We first describe our suggested hybrid robust-stochastic approach for a better understanding of our robust noise and air pollution routing problem (NPRP). Then the proposed deterministic NPRP model is formulated. After that, corresponding stochastic, and robust-stochastic according to this hybrid robust-stochastic optimization method are developed, which includes demand uncertainty in the model.

3.1 Hybrid Robust-Stochastic Optimization Methodology

First of all, to describe our proposed robust approach, the following mathematical programming model should be considered:

Model (I)

$$MAX : \mathrm{N}X + MY_s \tag{1}$$

Subject to:

$$AX = B, \tag{2}$$

$$CX + DY = F, \tag{3}$$

Based on two-stage stochastic optimization method [11], we can consider scenario-based parameters to address the uncertainty of parameters. For this purpose, variables are divided to the first and second stage. First stage variables remain unchanged, and the second may get different values in each scenario. As can be seen in the model (II), the objective function is expected value of scenarios, D_s is uncertain parameter, pr_s is scenario probability, X, and Y_s are the first and second stage variables respectively.

$$\begin{array}{ll} \text{Model (II)} & MAX : E[\mathrm{N}X + \mathrm{M}Y_s] = \mathrm{N}X + \sum_s pr_s \mathrm{M}Y_s \\ \textit{Subject to}: & \end{array} \tag{4}$$

$$AX \leq B \tag{5}$$

$$CX + D_s Y_s \leq F \qquad \forall s \epsilon \mathrm{S} \tag{6}$$

The scenario parameter sometimes does not have deterministic value in each individual scenario. In fact, $D_s \sim U(D_s - \delta_i \sigma_i, D_s + \delta_i \sigma_i)$ where σ_i is standard deviation and δ_i is a coefficient by which an uncertain parameter varies around its scenario value.

To tackle this kind of uncertainty in each scenario, we suppose to use a robust optimization approach. This approach is based on [12] which considers uncertainty model with a linear robust counterpart. The robust counterpart for the two-stage stochastic model (II) is as the following model (III):

$$\begin{array}{ll} \text{Model (III)} & MAX : \mathrm{N}X + \sum_s pr_s \mathrm{M}Y_s \\ \textit{Subject to}: & \end{array} \tag{7}$$

$$AX \leq B \tag{8}$$

$$CX + D_s Y_s + Z_s \Gamma_s + P \leq F \ \forall s \epsilon \mathrm{S} \tag{9}$$

$$Z_s \Gamma_s + P \geq \widehat{D}_s Y_s \qquad \forall s \epsilon \mathrm{S} \tag{10}$$

$$Z_s, P \geq 0 \qquad \forall s \epsilon \mathrm{S} \tag{11}$$

where $\boldsymbol{P}$, and $\boldsymbol{Z_s}$ are dual variables related to robust formulation and model convexity, and $\widehat{\boldsymbol{D}}_{\boldsymbol{s}}$ is the uncertain part of the parameter. To control conservatism level, parameter $\boldsymbol{\Gamma_s}$ is defined for every constraint $\boldsymbol{i}$ and employed in Model (III). This parameter takes any value in the interval $[0, |\boldsymbol{j_s}|]$, where $\boldsymbol{j_s}$ represents the set of uncertain parameters appeared in constraint $\boldsymbol{s}$. If decision maker choose $\boldsymbol{\Gamma_s} = 0$; accordingly, uncertainty of the model will be ignored completely while $\boldsymbol{\Gamma_s} = |\boldsymbol{j_s}|$ represents the hard worst case solution.

3.2 Formulation of the Base Deterministic Formulation

We now present a deterministic model for a pollution routing problem which takes into account noise emission equation and aims to minimize GHS emission as well as noise emission. We name this new extension of PRP as a noise pollution routing problem (NPRP).

In this problem, we have a heterogeneous fleet of vehicles with different capacity and technical features. The model is described as a complete direct graph $G = (N, A)$ with $N = \{0, 1, 2, \ldots, n\}$ as the set of nodes where node 0 assumed as a depot. d_{ij} denotes distance matrix between nodes i and j; moreover, D_i is a non-negative and uncertain parameter that shows the demand of customers and Q^w is equal to the capacity of each vehicle which cannot exceed m. In this problem, all customers have their own time window; therefore, the earliest and latest are a_i, b_i respectively.

Regarding air pollution, the PRP first time introduced by [2], and extended by [13]. They proposed the following formulation for calculating fuel consumption:

$$F(v) = \frac{\lambda(kNV + w\gamma\alpha v + \gamma\alpha f v + \beta\gamma v^3)d}{v} \tag{10}$$

Where v, d, and w denote vehicle speed, travel distance, and curb weight of an empty vehicle. Furthermore, the description and typical values of the other parameters related to road and vehicle specification can be found in [4]. From this formulation, it is obvious that fuel consumption strongly depends on payload and travel speed.

A noise prediction model called Harmonoise model was developed to be used by European Union members for noise mapping [14]. The equations for this models are presented below:

$$\begin{aligned} L_R(f) &= a_R(f) + b_R(f) log\left(\frac{v}{v_{ref}}\right), \\ L_P(f) &= a_P(f) + b_P(f)\left(\frac{v - v_{ref}}{v_{ref}}\right) \end{aligned} \tag{11}$$

In this formulation, $L_R(f)$ and $L_P(f)$ are function of frequency that denotes rolling and propulsion noise emissions respectively. Accordingly, v_{ref} is considered 70 km/h, and $a_R(f), b_R(f), a_R(f)$, and $b_R(f)$ are compensation factors for frequency. More information about this model can be found in [15]. In order to take into account the environmental factors such as road condition, a random parameter namely (GE_{ij}) between 0.5 and 1.2 is considered.

In this model, we aim to reduce over-threshold noise emissions. Moreover, there are some noise sensitive areas which should be addressed in this model such as hospitals, nursing home, etc. Modeling indices, parameters and decision variables are defined below.

Sets

I : Set of customers
W : Set of vehicle types
R : Set of speed levels
S : Set of scenarios

Parameters

d_{ij} : distance matrix from i to j
GE_{ij} : A coefficient to consider road condition on arc (i,j)
$[a_i, b_i]$: Time window for customer i

F_w : Fix cost for using vehicle type w
D_i^s : demand of customer $i \in I$ in scenario $s \in S$
v^r : Speed level r $\in R$.

Variables
VC_{w} : Number of vehicle type w $\in W$.
f_{ij}^s : Total amount of flow in arc (i,j) in scenario $s \in S$
z_{ij}^{rw} : A binary variable equals 1 if arc (i,j) is crossed by vehicle type w with speed r
x_{ij} : A binary Variable equals 1 if arc (i,j) appears in the solution
y_i : Starting time of service for customer i

The suggested bi-objective mixed integer linear programming model for NPRP which tries to minimize fuel consumption (Z^{fuel}), and noise emission simultaneously Z^{noise} is as follow:

$$Min\, Z = Z^{fuel} + \omega Z^{noise} \tag{12}$$

Subject to:

$$\begin{aligned} E\left(Z_s^{fuel}\right) = & \sum\nolimits_{s=1}^{S} Pr_s \Big(\sum\nolimits_{i=0}^{n} \sum\nolimits_{j=0}^{n} \sum\nolimits_{r=1}^{R} \sum\nolimits_{w=1}^{W} \tfrac{kNV\lambda d_{ij} z_{ij}^{rw}}{v^r} \\ & + \sum\nolimits_{i=0}^{n} \sum\nolimits_{j=0}^{n} w\gamma\lambda\alpha_{ij} d_{ij} x_{ij} + + \sum\nolimits_{i=0}^{n} \sum\nolimits_{j=0}^{n} \gamma\lambda\alpha_{ij} d_{ij} f_{ij}^s \\ & + \sum\nolimits_{w=1}^{W} \sum\nolimits_{r=1}^{R} \sum\nolimits_{i=0}^{n} \sum\nolimits_{j=0}^{n} \beta\gamma\lambda d_{ij} z_{ij}^{rw} (v^r)^2 \end{aligned} \tag{13}$$

$$Z^{noise} = \sum\nolimits_{i,j}^{n} NR_{ij} + \sum\nolimits_{i,j}^{n} NP_{ij} \tag{14}$$

$$L_{ij}^R = \sum\nolimits_{r,w} GE_{ij} (a_R^w(f) + \sum\nolimits_{r=1}^{R} b_R^w(f) log\left(\tfrac{v^r}{v_{ref}}\right) z_{ij}^{rw}) \quad \forall (i,j) \in N \tag{15}$$

$$L_{ij}^P = \sum\nolimits_{r,w} GE_{ij} \left(a_p^w(f) + \sum\nolimits_{r=1}^{R} a_p^w(f) \left(\tfrac{v^r - v_{ref}}{v_{ref}}\right) z_{ij}^{rw} \right) \quad \forall (i,j) \in N \tag{16}$$

$$L_{ij}^R - l_{ij}^R \le NR_{ij} \qquad \forall (i,j) \in N \tag{17}$$

$$L_{ij}^p - l_{ij}^P \le NP_{ij} \qquad \forall (i,j) \in N \tag{18}$$

$$\sum\nolimits_{i=0}^{n} x_{ij} = 1, \qquad \forall j \in N \tag{19}$$

$$\sum\nolimits_{j=0}^{n} x_{ij} = 1, \qquad \forall i \in N \tag{20}$$

$$\sum\nolimits_{j=1}^{n} \sum\nolimits_{w=1}^{W} z_{0j}^{rw} = VC_{w'} \qquad w' \in W \tag{21}$$

$$\sum\nolimits_{w=1}^{W} F_w VC_w \leq Budget \tag{22}$$

$$\sum\nolimits_{j=1}^{n} x_{0j} \leq m \tag{23}$$

$$\sum\nolimits_{j=0, j\neq i}^{n} f_{ji} - \sum\nolimits_{j=0, j\neq i}^{n} f_{ij} = D_i, \qquad \forall i \in N \tag{24}$$

$$D_j^s x_{ij} \leq f_{ij}^s \leq \left(Q^w - D_i^s\right) \sum\nolimits_{r,w} z_{ij}^{rw}, \qquad \forall (i,j) \in N \, \forall s \in S. \tag{25}$$

$$\sum\nolimits_{i,r} z_{ij}^{rw} - \sum\nolimits_{j',r} z_{jj'}^{rw} = 0 \qquad \forall j \in N, w \in W \tag{26}$$

$$y_i - y_j + t_i + \sum\nolimits_{r \in R} d_{ij} z_{ij}^{rw} / v^r \leq O_{ij}\left(1 - x_{ij}\right) \quad \forall i \in N, j \in N, i \neq j, \tag{27}$$

$$a_i \leq y_i \leq b_i \qquad \forall i \in N \tag{28}$$

$$y_i - s_{jw} + t_i + \sum\nolimits_r \sum\nolimits_w d_{ij} z_{ij}^{rw} / v^r \leq M\left(1 - x_{ij}\right) \forall i \in N, j \in N, i \neq j \tag{29}$$

$$\sum\nolimits_{r,w} z_{ij}^{rw} = x_{ij} \qquad \forall (i,j) \in A \tag{30}$$

$$\begin{gathered} x_{ij} \in \{0,1\}, NR_{ij}, NP_{ij}, f_{ij}, VC_w, y_i \geq 0, \qquad z_{ij}^{rw} \in \{0,1\}, \\ \forall (i,j) \in N, r \in R, \, and \, w \in W \end{gathered} \tag{31}$$

The objective function (12), minimize hazardous noise and total fuel consumption and formulations (13), (14) express the normalized fuel consumption and over-threshold noise objective functions respectively. (15) and Constraints (16), give us the rolling and propulsion noise emissions respectively while noise levels exceeding the threshold (l_{ij}^R, l_{ij}^P) are calculated in constraints (17) and (18). Constraints (19) and (20), enforce that each customer should be visited once and constraint (21) states amounts of hired vehicles which should not be exceeded from m, and Eq. (22) ensures the budget limitation. Constraints (24) to (26) ensure flow balance in each and constraints (26) to (28) enforce the time window limitations. Finally, speed level for each arc is determined in constraint (30).

3.3 Formulation of the Stochastic NPRP

Based on the presented approach in Sect. 3.1, we now intend to include demand uncertainty as uncertainty scenarios. This may lead to some changes in constraints. Accordingly, stochastic counterpart of the deterministic model introduced in Sect. 3.2 is as follow:

$$Min\, Z = E\left(Z_s^{fuel}\right) + \omega Z^{noise} \tag{32}$$

Subject to: (14)–(24), (26)–(31), and

$$E\left(Z_s^{fuel}\right) = \sum_{s=1}^{S} Pr_s \Big(\sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{r=1}^{R} \sum_{w=1}^{W} \frac{kNV\lambda d_{ij} z_{ij}^{rw}}{v^r} + \sum_{i=0}^{n} \sum_{j=0}^{n} w\gamma\lambda\alpha_{ij} d_{ij} x_{ij} + + \sum_{i=0}^{n} \sum_{j=0}^{n} \gamma\lambda\alpha_{ij} d_{ij} f_{ij}^{s} + \sum_{w=1}^{W} \sum_{r=1}^{R} \sum_{i=0}^{n} \sum_{j=0}^{n} \beta\gamma\lambda d_{ij} z_{ij}^{rw} (v^r)^2 \Big) \tag{33}$$

$$\sum_{j=0, j\neq i}^{n} f_{ji}^{s} - \sum_{j=0, j\neq i}^{n} f_{ij}^{s} = D_i^s \qquad \forall i \in N, \forall s \in S. \tag{34}$$

$$D_j^s x_{ij} \leq f_{ij}^s \leq \left(Q^w - D_i^s\right) \sum_{r,w} z_{ij}^{rw}, \quad \forall (i,j) \in N, \forall s \in S. \tag{35}$$

As can be seen in this model, parameter D_i^s represents demand uncertainties and constraints (33)–(35) are the control constraints. Demand uncertainty has influence on variable f_{ij}^s which can get different values in different scenarios realization.

3.4 Formulation of the Hybrid Robust-Stochastic NPRP (HRNPRP)

As described in Sect. 3.1, the final step of the suggested hybrid robust-stochastic NPRP model is shown in this part. Although we defined some scenarios for the uncertain parameter (D_i^s), exact estimation of its value in each scenario seems to be impossible in many cases. Therefore, a robust optimization method based on bound uncertainty is developed to address uncertainty in each individual scenario. The final HRNPRP model is as follow:

$$Min\, Z = E\left(Z_s^{fuel}\right) + \omega Z^{noise} \tag{36}$$

Subject to: (14)–(24), (26)–(31), (33), (35), and

$$\sum_{j=0, j\neq i}^{n} f_{ji}^{s} - \sum_{j=0, j\neq i}^{n} f_{ij}^{s} = D_i^s + P_i^s + \Gamma Z_i^s, \qquad \forall i \in N, \forall s \in S. \tag{37}$$

$$P_i^s + Z_i^s \geq \widehat{D}_i^s \qquad \forall i \in N, \forall s \in S. \tag{38}$$

$$P_i^s, Z_i^s, f_{ji}^s \geq 0 \tag{39}$$

4 Computational Experiments

In this section, in order to examine the performance of our suggested NPRP model, a well-known data set (PRPLIB) is used. This data set can be downloaded from the following website: http://www.apollo.management.soton.ac.uk/prplib. It is worthy to mention that GE_{ij} is generated randomly between 0.5 and 1.2 for each arc and l_{ij}^R, *and* l_{ij}^P are considered 52 to 71 dB randomly. In this research, three classes of light trucks are considered as vehicle categories and the parameters of these trucks extracted from [13].

Furthermore, optimistic and pessimistic scenarios are defined as 50% and 150% of the average demand respectively and the uncertainty level in each scenario is 10% (δ_i). We also set 0.2, 0.45, and 0.35 as scenario probabilities (pr_s). To solve the bi-objective model, we adopt a goal programming approach [16], and the proposed HRNPRP model solved using CPLEX solver embedded in GAMS 26.1 on a laptop with Intel Core i5 82050U CPU and 8 GB RAM.

Table 1. Comparison between PRP and NPRP (21-node instance)

Vehicle	PRP				NPRP			
	Type	Route	Z^{fuel} (L)	Z^{noise} (dB)	Type	Route	Z^{fuel} (L)	Z^{noise} (dB)
1	3	1-4-5-3-12-1	138	1050	1	1-4-20-1	168	315
2	3	1-9-7-2-18-1			2	1-17-18-1		
3	3	1-10-17-1			2	1-11-21-1		
4	3	1-11-8-15-13-1			2	1-15-9-5-1		
5	3	1-14-20-6-1			3	1-8-6-10-13-1		
6	3	1-19-21-16-1			3	1-16-14-7-2-1		
7	–	–			3	1-12-3-19-1		

The performance of the PRP and NPRP approach is depicted in Table 1. As can be seen in this table, by a 30-L increase in fuel consumption for the whole fleet, the over-threshold noise emission drops down from 1050 dB to 315 dB. Heavy-duty trucks have severe noise factors; therefore, it can be concluded that in order to reduce the amount of over-threshold noise emission, it is better to choose light-duty trucks. As reported in the solution by the NPRP model, to provide enough capacity to fulfill customer demand, one more truck is required. Nevertheless, in this solution, three vehicles out of 7 are heavy-duty (type 3).

In Fig. 1, the performance of the suggested model is examined under four different data sets with 10 and 15 Nodes. For this purpose, a realistic conservatism level $(\Gamma = 0.5)$, and five weight values $(\omega = 0, 0.5, 1, 2, 5)$ for noise objective function are given. It should be noted that in this model $\Gamma = 0$ is the most optimistic, and $\Gamma = 1$ is the hard-worst case scenario. As it is evident in this figure, considering the noise objective function, and interval uncertainty in each scenario, make significant modification in the results, which consequently lead to robust and sustainable solutions. Furthermore, it can be concluded that for a realistic DM $(\Gamma = 0.5)$, $\omega = 1$ is a reasonable option, because we do not see a significant modification in noise emission but in fuel consumption.

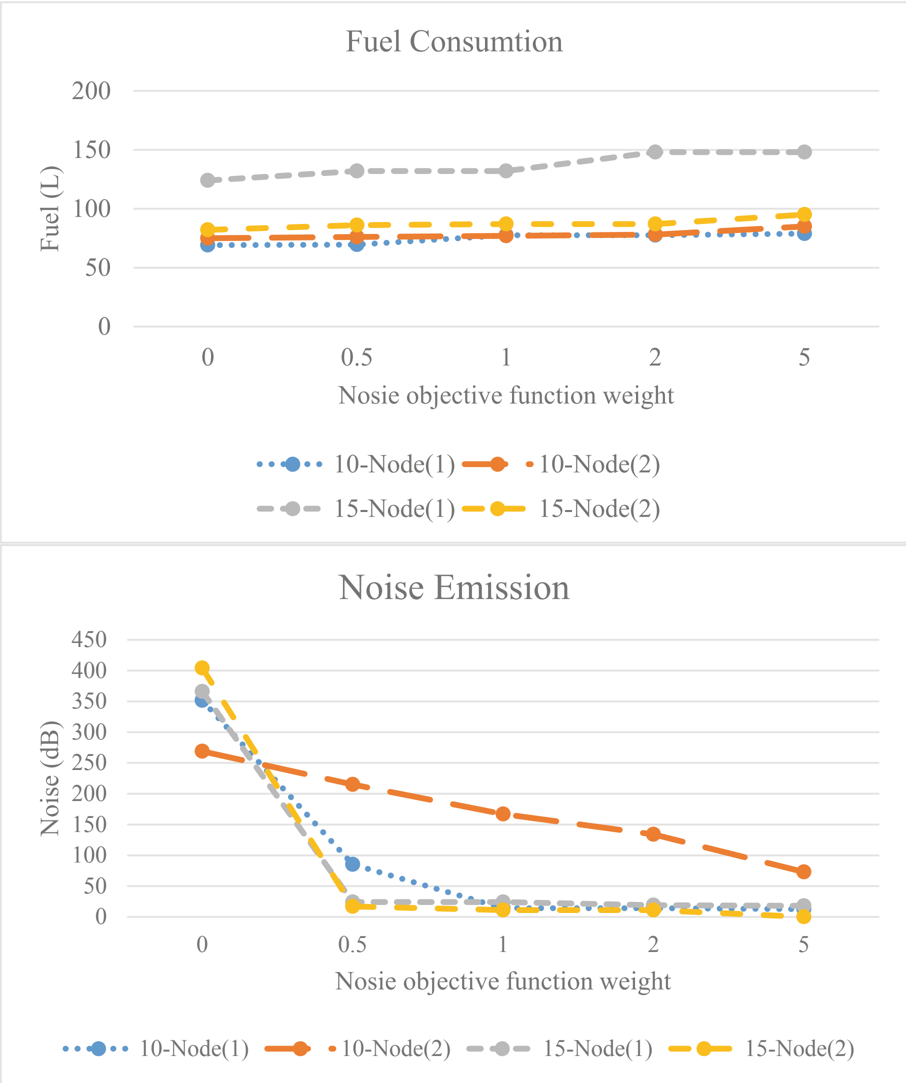

Fig. 1. Noise emission and fuel consumption in a realistic conservatism level $(\Gamma = 0.5)$

5 Conclusions

In this paper, we developed a mixed-integer programing model for robust noise and air pollution routing problem considering demand uncertainty. We developed a new robust-stochastic approach to address interval uncertainty of scenario parameters in each individual. Furthermore, a real-world data sets in order to evaluate the proposed model and analyze the noise emission effects on vehicle routing problem adopted. Final results approve that including noise pollution in PRP models is relevant and suggested

HRNPRP model can reduce noise emission significantly. Moreover, it is worthy to be mentioned that considering fuel consumption as the only term in the objective function may result a solution with high noise pollution value. For future researches, solution algorithms for solving large-scale problems as well as considering vehicle reliability is recommended.

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