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Research Article

A Meta-heuristic Model for Optimizing Goods Transportation Costs in Road Networks based on Particle Swarm Optimization

Farhad Hadadi[#]* and Hamid Shirmohammadi[#]

[#]Highway and Transportation Engineering, Civil Engineering Department, Urmia University, Urmia, Iran

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Abstract

Road transportation network system plays a significant role in transportation of goods with economical aspects. Most manufacturers' products and costumers' needs are transported by transport organizations. But, one of the most concern of many goods transport organizations is to reduce the high costs of transporting goods that imminently impose heavy expenditures and accordingly lessen presentation of an acceptable service to the costumers. Many efficient optimization methods such as particle swarm optimization (PSO) and genetic algorithms (GA) which optimize costs (serviceability, tax, repair of vehicles, fueling, etc.) should be taken into account. The aim of this study is to optimize goods transportation costs from origin to destination centers via PSO Algorithm. This algorithm quickly finds paths with the lowest costs. After applying the algorithm, the results will be categorized into separate equations. Also, from the statistical view, the most optimized equation will be selected. Therefore, an optimal rate in the range of 0.90% and 1.54% has been introduced as a minimizing formula for total monthly costs while the population of vehicles is growing. This formula affects positively reduction of goods transportation costs for a high optimal rate in this paper.

Keywords: *Road transportation network system; Goods transportation costs; Transportation network optimization; PSO algorithm*

Introduction

Transportation of goods is one of the main parts of economy which supports commercial and productive activities by effective movement and accessibility to the pure and consuming goods. Transportation supports an important domain of products services from manufacturers to users' centers so that remarkably each country supplies its economic activities in industrial zones based on freight costs (Crainic & Laporte, 1997). The ideal transportation system should have an efficient performance in services quality and economical efficiency and all transport organizations must consider their goods delivery time with the cost of service quality. Furthermore, goods transportation must be compatible with political, social and economic changes. But, low cost is the reason that causes a dramatic investment simply in one kind of transportation mode. Among goods transportation systems, road transportation system is a good choice for transportations inside the countries since nowadays most of the countries are encountering economical problems which require lower investment with more efficiency and the advantage of the door to door or storage to storage services. Most of the economists believe in road transportation for carrying stuff or people from the rural regions rather than railway, waterway and airway systems. Road transportation services are flexible with various major advantages. For example, this type of transportation system is appropriate for short distances and products could be straightly loaded and unloaded into vehicles.

Moreover, fragile goods could be easily carried by this sort of transportation system that is faster than waterway and railway transportation. Less wrapping technologies and costs in comparison with other transportation modes is sanother utility of road transportation network. A report completed by U.S department of transportation in 2009 (U.S. Department of Transportation 2007; Commodity Flow Survey 2009) indicates that road transportation network system is more effective and economical for freight distribution among modes by ton-miles, tons, and value (see fig. 1.a, fig. 1.b and fig. 1.c). Although road transportation gets convenient and inexpensive through other transportation modes, it needs optimizing in order to become more common and efficient. The history of road transportation network

*Corresponding author **Farhad Hadadi** is Master student, and **Hamid Shirmohammadi** is working as Assistant Professor

backs to the ancient civilization era. In the first and second world wars particularly at the beginning of the industrial revolution, road transportation networks played a vital role in supplying battle grounds needs. But, over the time, the management and optimization of road transportation network have been planned to satisfy mobility business objectives. Today, official governments gradually allocate all plans and budgets in private sectors to increase their capacities for responding to demands and decrease transporting costs just through sending goods directly to trucks by cross-ducking infrastructures. To take profit in transportation networks, the energy costs, time and environmental impacts should be optimized. In recent years, there has been a growing trend toward a balanced optimization across a number of goals.

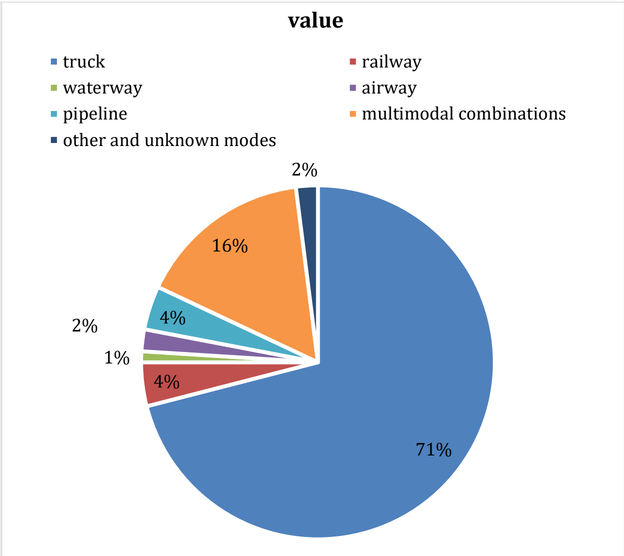

Fig. 1.a Freight distribution by value in 2007 in U.S

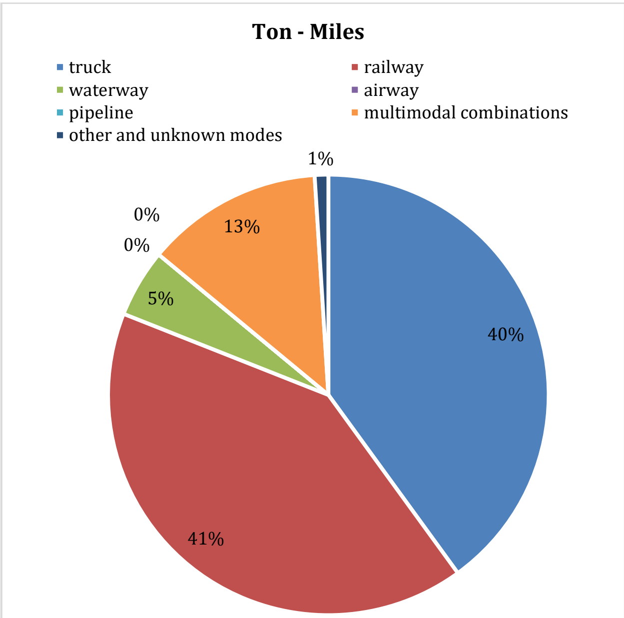

Fig. 1.b Freight distribution by ton–miles in 2007 in U.S

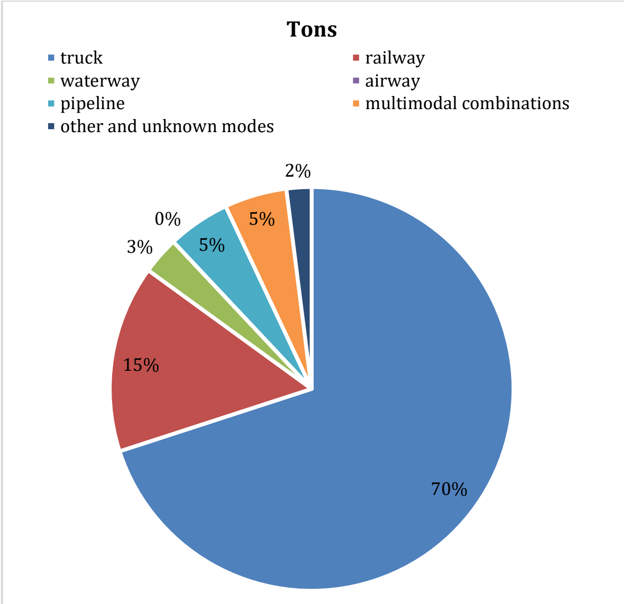

Fig. 1.c Freight distribution by tons in 2007 in U.S

The globalization of trade and supply chains has developed transportation networks rapidly so that the measure and intricacy of transportation networks have been enhanced significantly in the last decade. To identify transportation network optimization is difficult and an intricate problem to unravel. For example, optimization is not usually usable or really accessible for the problems classified as NP-hard problems. Other optimization methods have been improved and utilized. The minimum-cost path problem is a specialization of the optimization of transportation networks. It is a popular optimization model with the goal of detecting a possible path of minimum cost in a network with capacity limitations and side costs (Goldberg & Tarjan, 1987). Several methods to trade-off accurately with speed have been designed as the following: (a) applying systems with equilibrium paths instead of user equilibrium (UE) ones (Sheffi, 1985) in the network loading (Steenbrink, 1974b; Dantzig *et al.*, 1979; Chen & Sul Alfa, 1991); (b) presuming constant linkage cost functions (Boyce *et al.*, 1973; Holmberg & Hellstrand, 1998); (c) decreasing integer constraints on decision variables (Steenbrink, 1974b; Abdulaal & LeBlanc, 1979; Dantzig *et al.*, 1979); (d) analyzing the problem (Steenbrink, 1974b; Dantzig *et al.*, 1979; Hoang, 1982; Solanki *et al.*, 1998); (e) using link and node abstraction or extraction in order to accumulate the network (Haghani & Daskin, 1983); (f) applying an innate nearness to short paths by determining a substitute problem in which the intricacy in the original one is absent (Yang & Bell, 1998); (g) heuristic methods (Poorzahedy & Turnquist, 1982; Chen & Sul Alfa, 1991; (h) meta-heuristic (evolutionary) methods such as genetic algorithm (GA) (Yin, 2000), simulated annealing (SA) (Lee & Yang, 1994), GA, SA, and Tabu search (TS) (Cantarella *et al.*, 2002), ant colony optimization (ACO) (Poorzahedy & Abulghasemi, 2005); (i) hybrid meta-heuristics such as hybridized ACO (HACO) with GA, SA, and TS (Poorzahedy &Rouhani, 2007).

Literature review

It is well known that linear programming problem could be typically unraveled by applying popular algorithms from linear programming theory such as simplex method, branch, bound or cut and etc. However, it is acceptable to have an unraveling method that is hypothetically warranted to be the best. Such accurate methods are not mostly usable. Once the complexity of the model rises (i.e. most of the time, NP-Hard problems be unraveled precisely), or likely time or simply the present resources are restricted, then using an exact method is not always possible or a possible unraveling scheme. In outlines where to utilize exact methods is not possible, to find out a rough unraveling will suitably be acceptable, particularly if the detected unraveling is near to the optimal one and time or engaged resource that are rational. It is often practicable to plan specific heuristics; heuristics means to take benefit of special problem characteristics or employ historical science obtained from the past experiments. So obviously, the qualities of such heuristics are highly relies on the amount of extent learning and present tests in the design of the algorithm. Closeness procedures based on general heuristics have been significantly increased in recent years. These methods are adequate across the problem scope and often result in better implementation compared to specific heuristics specifically in terms of unraveling quality and performance time. In the literature, it is possible to detect a trend towards the application of meta-heuristic closeness methods as the unraveling basis for solving transportation network problems. The most popular closeness methods consist of (Multi-Objective), Genetic Algorithm, (Fuzzy) Ant Colony Optimization and Particle Optimization Swarm. One example of transportation network optimization is the transshipment problem of cross-docking networks where the goods are delivered from goods producers to customers through cross-docking infrastructures without stocking them in distribution centers. Here the goal function is to minimize the transportation costs in the network by loading trucks in the supplier locations and sending them to customers directly or indirectly using cross-docking infrastructures where loads are fastened (Musa *et al*., 2010). Detecting the shortest distance distribution on a given network is the most popular aim in transportation network optimization, i.e. an optimal set of tracks has been specified between suppliers and customers (Han & Ji, 2010). However, there is a growing interest in applying optimization elements like profit, energy, service level or flexibility, etc. In this paper, Particle Swarm Optimization (PSO) is selected as the optimization method. It is originated from two main part methodologies. The most evident potential is probably its relations with artificial life (A-life) and in general birds flocking or fish schooling, and swarming theory in particular. However, it is also related to evolutionary calculations and to both genetic algorithms and evolutionary plans (Kennedy & Eberhart, 1995). PSO based scheme have been used to the unraveling of multi-goal transportation network optimization problems. A Fourth-Party Logistics (4PL) network optimization model based on flexibility and a PSO method to unravel the problem was draw and utilized (Huan *et al*., 2011). A resembling scheme is adopted to expand an unraveling methodology for the production and distribution planning of a multi-echelon unequaled supply chain (Che, 2012). Moreover, there is a progressive PSO method (Zhao & Dou, 2011). In this method, origin and destination of goods are presumed like each bird's nest so that any bird likely could find food out with speed but a group of them will change their position all together.

Typical Mathematical Model of Logistics Vehicle Routing Problems to optimize goods costs

In this research, just in road transportation system trucks are arbitrarily selected to represent heavy vehicles. If there is a distribution center with N truck, each truck load will be q_n (n= 1, 2,..., N), delivery to customer L in distribution center, demand of any customer's good is represented as g_i (I = 1, 2,..., L) and max $\{g_i\} \leq$ max $\{q_n\}$. Path optimization aims to transport through the possible shortest path. Additionally, if the segregated distribution center encoding is 0, the staff is encoded as 1, 2,..., L. Similarly, variables are defined as:

$$X_{ijn} = \begin{cases} 1 & \text{Vehicle n is driven by customer i to j} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

$$y_{ijn} = \begin{cases} 1 & \text{The customer i tasks finished by vehicle n} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

A point from i to j of transportation costs is named as c_{ij} which can be represented as a path, time, etc. In this paper, it is tried to select a rationale path and make the whole transport path as short as possible in order to diminish the costs of transportation. Thus, c_{ij} is specified as a driving distance for each truck and z is defined as the driving distance of all trucks. The arithmetical model is set up in the following assumptions (Jiang and Li, 2010):

$$\text{Minimize} = \sum_{i=0}^{L} \sum_{j=0}^{L} \sum_{n-1}^{L} c_{ij}\, x_{ijn} \tag{3}$$

$$\text{S.t} \begin{cases} \sum_{N=1}^{N} y_{in} = \begin{cases} 1 & i = 1, 2 \ldots L \\ N & i = 0 \end{cases} & (5) \\ \sum_{i=1}^{N} y_{ijn} = y_{jn} \;\; j = 1, 2 \ldots L{:}\ k = 1, 2 \ldots k & \\ \sum_{j=1}^{N} y_{ijn} = y_{in} \;\; I = 1, 2 \ldots L{:}\ k = 1, 2 \ldots k & (6) \end{cases}$$

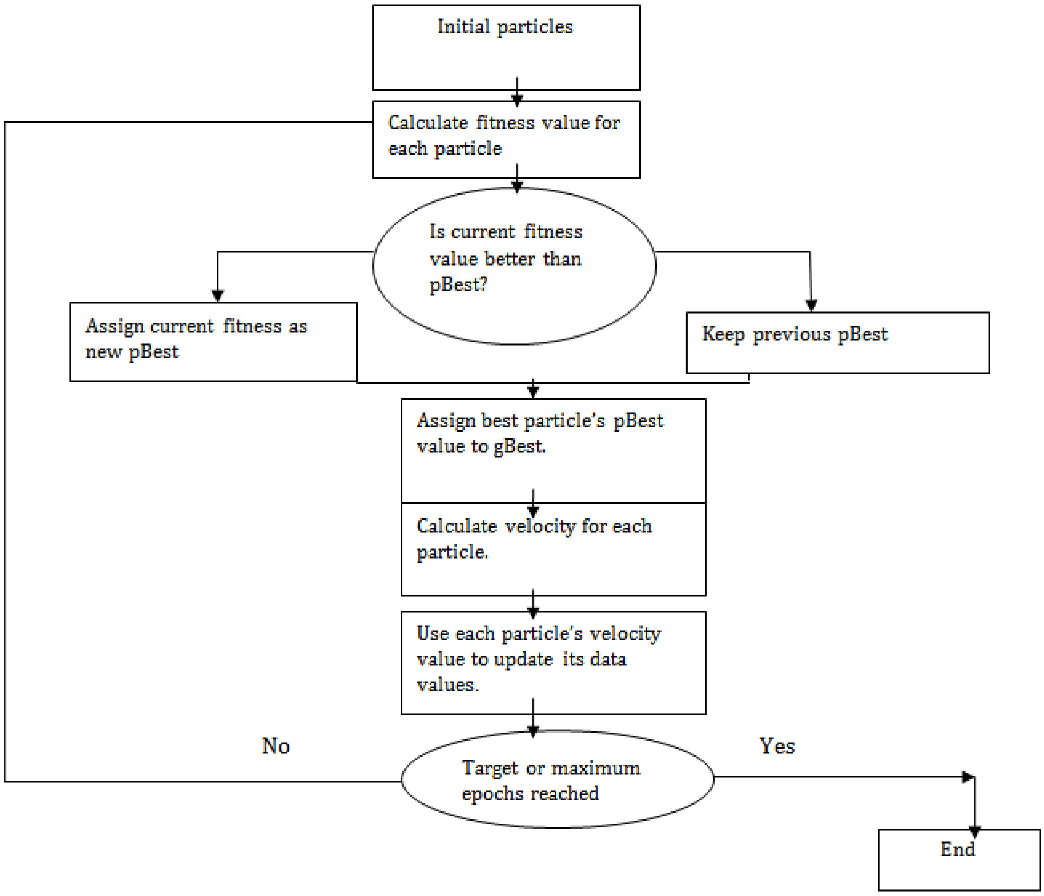

Fig. 2 Flow Chart of Particle Swarm Algorithm

All vehicles such as light and heavy vehicles carry goods from origin to destination centers for delivery and when finished thy return to the distribution center. Road transportation has the same capacity and each requirement capacity for responding to customer's demand is not more than the vehicle loading capacity; each customer's service for delivering goods by transportation organization is completed just by one service request. For achieving all above conditions, it is necessary to minimize **z** function with the proposed assumptions.

Research Methodology

In this research, we used Particle Swarm Optimization (PSO) that is a minimization method by which problems that their answer will be a point or surface in the N-dimensional space could be experienced. In this space, assumptions are designed then an initial speed allocates to them. Also, a linkage channel between particles is considered. Subsequently, these particles respond to the space for moving and result from this movement according to a merit criterion calculation. In few minutes, the particle will accelerate to particles with high merit criteria and in the same linkage group. This kind of mathematical optimization successfully solves all continuous optimization problems. Although this is not an old method, it is so prominent and economical. PSO is similar to evolutionary algorithms like GA[2] in a sense that it begins with contingently generated solutions and develops gradually the solution up to a favorable one. However, unlike GA, the evolutionary procedure in PSO just evolves the locations of the particles rather than engendering new particles (Shi & Eberhart, 1998a). The most popular capability of PSO is its fast closeness which is evaluated positively with many meta-heuristics such as GA and SA[3] (Abraham et al., 2006). Moreover, it may be quickly executed and needs few parameter settings and computational memory (You, 2008). PSO has been successfully used in many areas (Voss & Feng, 2002; Jiang et al., 2007; Yisu et al., 2008). Fig. 2 shows PSO Algorithm:

- [x*] = PSO ( )
- *P* = Particle_Initialization ( );
- For *i*=1 to *it_max*
- For each particle *p* in *P* do
- *fp* = f(*p*);
- If *fp* is better than f (*pBest*)
- *pBest* = *p*;
- End
- End
- For each particle *p* in *P* do
- $v = v + c_1*rand*(pBest - p) + c_2*rand*(gBest - p)$;
- $p=p+v$;
- End
- End

[2] Genetic Algorithm

[3] Simulated Annealing

p: particle's position.
V: path direction.
c_1: weight of local information .
c_2: weight of global information.
pBest: best position of the particle.
gBest: best position of the swarm.
R*and*: random variable.
The number of particles is usually between 20 and 100.
C_1 is the importance of personal best value.
C_2 is the importance of neighborhood best value.
Usually $C_1 + C_2 = 4$ (empirically chosen value).
If the velocity is too low → algorithm will be too slow.
If the velocity is too high → algorithm will be too unstable.

The best solution can be explained by local best that is controlled by the current particle, while the best solution that has been found by the group is denoted by global best. The global best perceptually links all particles together. Each particle is affected by the best solution in the whole population; the local best is used to take into account the ability of each particle to remember its past individual successes (Voss & Feng, 2002) where w is named as the inertia weight that was firstly engaged in the range of 0.9–1.2 (Shi & Eberhart, 1998a), and c_1 and c_2 are constant values that were originally set to 2 (Eberhart & Kennedy 1995). These two constants become manifold by the random amount r_1 and r_2, relatively, which are used to keep the variety of the population, and are in the same distribution in the interval [0, 1] (Abraham *et al.,* 2006). Usually, $C_1 = C_2 = 2$ is used as default values (Abraham et al., 2006), while the research by Clerc and Kennedy (2002) indicates that using a larger parameter c_1 than a parameter c_2, but with $c_1 + c_2 \leq 4$, may have better implementation.

Implementation, optimization of goods transportation costs in MATLAB software

PSO algorithm is implemented via MATLAB software with Intel Core 5 due 2.53 GHz processor. In all experiments, PSO parameters are set as shown in table 1.
N= number of Trucks or population size for trucks.
Iteration = for doing a correct operation, it is necessary to run the program in 100 times.
Variable = annual costs such as fuel, freight, and repairs from origin and destination centers.

Table 1 Parameters Settings

Parameter	Setting
Population size	20, 40, 60, 80, 100
Number of iterations	100
Initial w (Inertia Weight)	1
Inertia Weight Damping Ratio	0.99
c_1 (Personal Learning Coefficient)	1.5
c_2 (Global Learning Coefficient)	2

Particles roam in the space, convey good positions to each other and adjust their own positions and velocities based on these good positions (see fig. 3) (Abraham *et al.,* 2006).

$$V_i^{t+1} = \underbrace{v_i^t}_{\text{Inertia}} + \underbrace{c_1 U_1^t (pb_i^t - p_i^t)}_{\text{Personal influence}} + \underbrace{c\_2\, U\_2\text{^}t\, (gb\text{^}t - p\_i\text{^}t)}_{\text{social influence}} \qquad (7)$$

And position change equation from a place to another place is:

$$P_i^{t+1} = P_i^t + V_i^{t+1} \qquad (8)$$

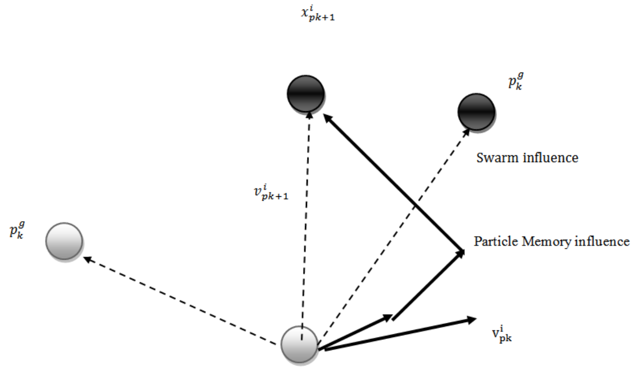

Fig. 3 Particle Swarm Optimization Motion

Computational application

In the application, the usefulness of the proposed model is shown for goods transport purposes between a start node (origin) and the end node (destinations). There are different nodes and possible linkages between them (see table 2). The road transportation mode is also considered in the model application. Costs of the linkages between the network's nodes have been gathered monthly (see table 2).

Table 2 Goods Costs between Nodes of the Road Network

Start node	End node	Transport mode	Goods cost ($ month)
1	4	Truck	65240
	5	Truck	95240
	6	Truck	98340
2	6	Truck	69540
	3	Truck	70100
	5	Truck	71230
3	4	Truck	72410
	5	Truck	76500
	2	Truck	77200
4	5	Truck	78210
	5	Truck	76500
	3	Truck	79320
5	4	Truck	80320
	2	Truck	82100
	3	Truck	83200
6	5	Truck	84520
	1	Truck	91200
	4	Truck	98270
Maximum		Truck	98700
Minimum		Truck	65240
Total costs		Truck	1449440

By inserting monthly costs into the model, the software will solve the problem according to the algorithm and subsequently find out the best and optimal cost due to some mistakes made by official organizations in estimating the cost. This model seems to be correct to detect the lowest costs.

Experimental Results

In table 3 which demonstrates mathematical equations, analytical and statistical science are considered properly, It can be understood that whatever times pass and the population of trucks increases, equations get more effective, exact and optimized with an acceptable reliability (see fig. 4 and fig. 5).

Table3 Analytical data From the Software

No.	N	Iteration	R-Squared (R^2)	Equation (Best Cost Optimal Function, $/month)
1	20	100	0.7954	$0.06x^3+0.09x^2+10x-10.4\,e(x)+14$
2	40	100	0.9087	$0.06x^3+0.09x^2+10x-8.9e(x)+14$
3	60	100	0.9017	$0.06x^3+0.09x^2+10x-11.5\,e(x)+14$
4	80	100	0.9565	$0.06x^3+0.08x^2+10x+0.4\,e(x)+14$
5	100	100	0.9579	$0.06x^3+0.08x^2+11x+8.8\,e(x)+14$

According to the table 4, it's clear that a mathematical equation that closely becomes close to the optimal solution will be the fifth equation because of the R-Square in 100 iterations (see fig. 5). To achieve the optimized equation, there are many optimization methods to minimize costs of goods in 100 iterations. However, the recommended algorithm plays an effective role as time passes. It provides the power of PSO optimization algorithm for minimizing goods transportation costs in road networks to deliver high-quality services to the costumers.

Table 4 Fitness of Equations

Equation number	SSE[4]	Adjusted R-square (R^2)	RMSE[5]
1	1.585e+25	0.7933	4.022e+11
2	1.873e+25	0.9078	4.372e+11
3	2.137e+25	0.9007	4.67e+11
4	1.758e+25	0.9561	4.236e+11
5	1.687e+25	0.9575	4.148e+11

SSE and RMSE in table 4 show statistical analysis for assessing the correct prediction of each equation. From the table 4 we can see low error in calculations with high R- Square are true statistical criteria to select the best predictative and exact model in optimizing costs by means of best cost optimal function as the fifth equation in table 4 has these characteristics.

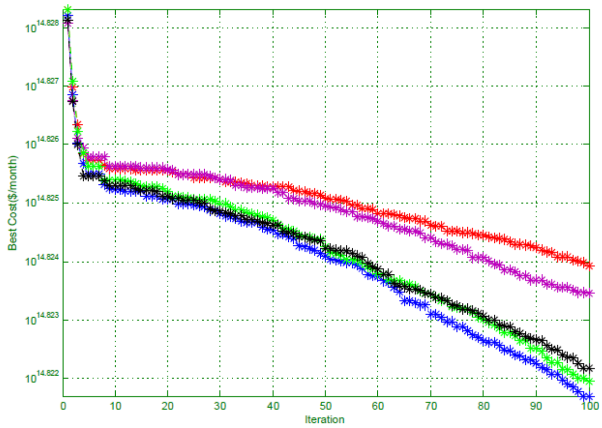

Fig. 4 The most Optimized Equation (Equation 5, N = 100)

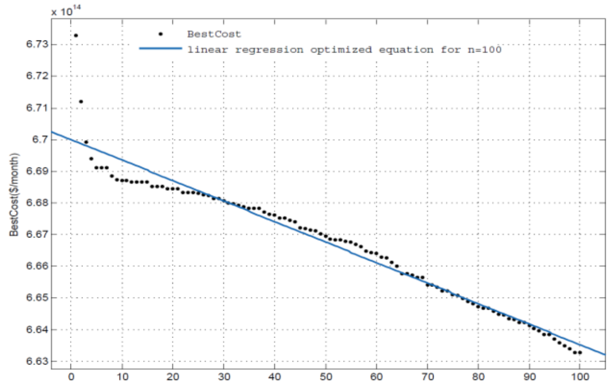

Fig. 5 Regression Optimized Equation in 100 Iterations

Furthermore, maximum and minimum costs in transporting goods for N truck under 100 iterations displayed by fig. 6 to clarify the influence of the proposed model with growth of trucks population. To reach an optimal rate in goods transportation costs, the following formula should be defined:

Optimal Rate of Goods Transportation Costs

$$=\frac{\text{Maximum Optimized Cost} - \text{Minimum Optimized Cost}}{\text{Maximum Optimized Cost}} \quad (5)$$

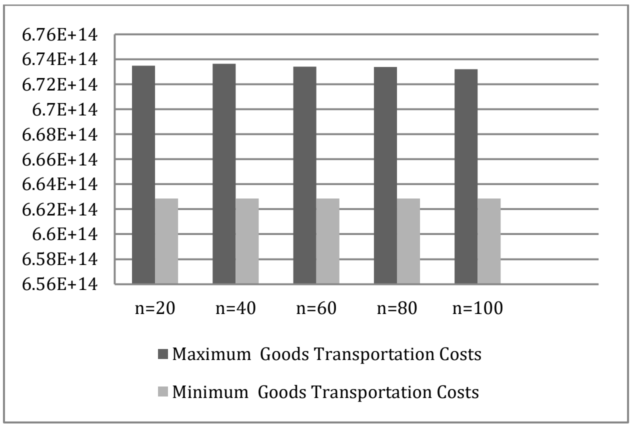

Fig. 6 Maximum and Minimum Goods Transportation Costs for N Truck

[4] Sum Squares Error
[5] Root Mean Square Error

Table 4 and fig. 7 illustrate that as the number of heavy vehicles (trucks) increases, the rates for 100 iterations in N truck regularly appear to lessen properly all goods transportation costs.

Table 5 Optimal Rate of Goods Costs for N Truck (from origin to destination centers)

Number of trucks	Optimal Rate of Goods Transportation Costs
n= 20	0.94%
n= 40	1.26%
n= 60	1.30%
n= 80	1.50%
n= 100	1.54%

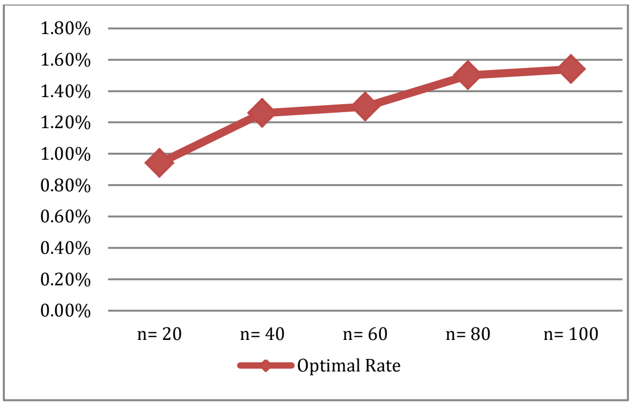

Fig. 7 Optimal Rate of Goods Transportation Costs for N Truck

Conclusion

Applying the PSO algorithm implies the effectiveness of this method to optimize goods transportation costs from origin to destination centers which is a top concern of transport organizations. The potential results of this research reveal an optimal rate in the range of 0.94% to 1.54% in costs for N truck with 100 iterations (see table 5). According to the fig. 7, the number of trucks increases in road networks. Regularly, the popularity of this method becomes more effective in optimizing costs while a high optimal rate is selected. First, the aim of the PSO is introduced. Second, assumptions are considered according to the monthly costs of the vehicle (fuel, repair, tax and etc.). By using the software (MATLAB) for running the algorithm, all data is entered and the experimental results of this study provide an optimized equation (see fig. 4) in comparison with other equations due to the influence of an arithmetic model with an acceptable reliability according to statistical and analytical examinations. Finally, this paper tends to present an optimal model to be used for estimating and optimizing monthly goods transportation costs in all national and private transport organizations in order to reduce high costs for hauling goods. However, in the future, other optimization algorithms might be created that would be more efficient, economical and quicker than PSO. But they should facilitate input data and eliminate extra constraints that will make algorithms more complex and likely will be more time consuming.

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