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A Multi-Facility AGV Location-Routing Problem with Uncertain Demands and Planar Facility Locations

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Abstract

The Location Routing Problem (LRP), Automatic Guided Vehicle (AGV), and Uncertainty Planner Facility (UPF) in Facility Location Problems (FLP) have been critical. This research proposed the role of LRP in Intelligence AGV Location–Routing Problem (IALRP) and energy-consuming impact in CMS. The goal of problem minimization dispatching opening cost and the cost of AGV trucking. We set up multi-objective programming. To solve the model, we utilized and investigate the Imperialist Competitor Algorithm (ICA) with Variable Neighborhood Search (VNS). It is shown that the ICAVNS algorithm is high quality effects for the integrated LRP in AGVs and comparison, with the last researches, the sensitivity analysis, and numerical examples imply the validity and good convexity of the purposed model according to the cost minimization.

Keywords: Location-routing, Automatic guided vehicle, Stochastic programming, Uncertainty, Meta-heuristic algorithms.

1 | Introduction

Automated guided vehicle and supply chain management are one of the most important components of productivity and efficiency in the organization's units [1]. In the JIT system, the materials and services required for the project should be provided at the on-time they are needed, as a result of a significant reduction in waste of time and loss of time and storage. Nowadays in many projects such as production projects, leasing, etc. Which utilize automated guided vehicle management systems during times of uncertainty of supply chain demand, the supply of raw materials, manpower, machinery, and others planning the right things when they want to meet the needs of the plan. The order flow usually begins when the project implementation team starts the request. In these conditions, the process of purchasing and managing an AGV is organized in terms of demand uncertainty based on demand pull. One of the applications of AGV management is to apply its mechanisms in designing the optimal model for despatching locations and routing construction projects such as production projects.

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In automated vehicle management planning for the optimal design of production and inventory routing models, must be cover the three overlaps: material and service time requirements, software mechanisms, and timing of available cash flows. Adjusting the scheduling of purchases and ordering them is easier with the cash flows needed. All constraints must be considered in the planning process. One of the most important constraints is the ability to liquidate and restrict access to capital.

To reduce the negative impact of this restriction, the project's financial plan, purchasing, and managing automated guided vehicle agreements with suppliers should be concluded together. Also, in automated vehicle management planning, in terms of demand uncertainty, supply chain processes such as the supply of products and services required by the project from within or outside the organization are considered. Goli et al. [27] provided a framework for supply chain managers in crisis, who face similar problems in other environments, with valuable insights. At this step, we should have complete documentation of the factors that influence the process of purchasing and managing AGV, including understanding the methods of AGV management, the type of products or services required, the quantity and quality that they required, and their time of preparation [43]. Mohajeri et al. [51] purposed a fuzzy mathematical model is applied to an illustrative example of an uncertain closed-loop Green Supply Chain (GSC). However, in this study, this challenge is addressed to present a hybrid meta-heuristic algorithm using AGV routing and an intelligent model for AGV routing in planner facility with demand uncertainty conditions and locations. In this paper, the challenge is that many routes in routing can be sent back to the products by the facility and then to the distribution centers of the automated routing approach to be transferred to the manufacturer or intermediaries or waste and waste recovery companies.

Our costs include AGV transportation, energy consumption, and opening the number of depots is minimized when we can predict the location of the demand. To the last researches, there are only a few manuscripts in this field and our study is amongst the first modeling efforts, which aims to consider AGV-Location Routing (ALRP) and facility uncertainty demand and location with multi AGV, simultaneously. In effect, a simultaneous approach to both AGV dispatching location-routing and urban distribution depot location is believed to provide an optimal solution to the problem. Moreover, in this paper stochastic approach is implemented to rival uncertainties. Therefore, in real-world problems, the location of facilities is supposed as a function of the offered best AGV to an operation by some production operations and it's unknown. The developed model illustrates AGV assignment strategies and dispatching opening decisions, which minimizes the total cost in such an unreversed situation. The main novelty of this research is outlined as follows:

- *Studying the role of LRP in Intelligence AGV Location–Routing (IALRP) and energy-consuming impact in CMS.*
- *Addressing the uncertain demand of the problem by applying the Stochastic Programming (SP) approach.*

Demonstrating the applicability of the proposed model by designing and implementing an efficient hybrid ICA (GICA/VNS).

Simulating the best level of parameters of employed meta-heuristic by the Taguchi method as well as four assessment metrics.

Validation of the performance of the developed model by some sensitivity analyses.

Considering the complexity of the joint location routing of AGVs and uncertainty demand, assumptions are made to simplify the problem. The most common ones are:

- *Each AGV is available at the start of the assignment period.*
- *The routing of each facility type is available before making transportation decisions.*
- *All AGVs can service all type of facility operations in each of periods.*
- *The specified input/output buffer space is assumed at each machine and the load/unload stations, i.e. the limited buffer capacity is considered.*
- *AGVs move along Euclidean distance, with the assumption of no delay due to the disorder.*
- *Facility breakdown and AGV failure are ignored.*
- *All demands have equal value for transportation.*
- *Each vehicle simultaneously supports just one facility but the job facility can have more than one vehicle.*

The road map of the research illustrated, Section 2 presents the last literature on the types of LRP design and highlights the novelty of this paper to the last studies. The problem statement and model formulation are described in Section 3. Section 4 illustrates the implemented approaches and solution method for both combined the illustrated MIP model and statistical and uncertainty distributional information. Experimental evaluation and data generation, new meta-heuristic approach, chromosome coding, and the output of the developed model to samples and sensitivity analyses are described in Section 5. Finally, Section 6 deals with the conclusion and suggestion for further research directions in this study.

2 | Literature Review

Reveliotis [56] proposed a bi-directional path processing in a conflict resolution strategy, which ensures robust AGV conflict resolution. Other works that novelty significantly are Bish et al. [8], Hsu and Huang [37], Christopher et al. [13], Krishnamurthy et al. [37], Naiqi and Zeng [65], Lim et al.[42], Singh and Tiwari [58], Qiu et al. [67] and Taghaboni and Tanchoco [62]. Akturk and Yilmaz [3] presented jobs and vehicles scheduling decision-making hierarchy by Micro Opportunistic Approach (MOSA). Qiu and Hsu [52] proposed an algorithm for AGVs routing and schedule on a bi-directional path layout. The research is not sufficient to integrate the efficient routing algorithm with a path layout design that will route AGVs along a bi-directional in the shortest path available time. Haleh et al. [28] presented a problem that can be modeled as a job shop where the jobs have to transport between machines by AGVs.

Researchers	Scheduling	Routing	Type of Vehicles	Stochastic Parameter	Objectives
Jerald et al. [35]	MH		MV	-	MIT, MC
Jerald et al. [34]	AI		SV	-	MIT, MC
Guan and Dai [26]		S	MV	-	MDA
Gamberi et al. [22]		S	SV	-	MHTC
Dai et al. [11]		S	SV	-	MTT
Tavakkoli-Moghaddam et al. [64]		MT	MV	-	MM
Farahani et al. [77]		MT	MV	-	MMW
Yahyaei et al. [71]		AI			MC
Fazlollahtabar and Mahdavi-Amiri [19]		AI			MTT, MC
This research	**ALRP**	**MT-MILP**	**MV**	**FD**	**Min. MIT, MC, NV**

Vis [67] reviewed the literature on design and control issues related to AGV systems in the manufacturing, distribution, and transport systems. It is concluded that the majority of models can be used at manufacturing centers for design problems. Some of these models and new models in large AGV systems have already proven successful. Hasan [29][3 Introduced the AGV routing problem with highlighted shortest path and AGV routing using Local Position System (LPS) in real-time in the lab view environment is obtained. Some of the last reviews Fazlollahtabar and Saidi-Mehrabad [21], Hasan [29], Le-Anh and De Koster [39], Vis [67], Vivaldini et al. [68] classified in *Table 1*.

Table 1. Review of the previous studies on the AGV location-routing problem.

Researchers	Scheduling	Routing	Type of Vehicles	Stochastic Parameter	Objectives
Za Remba et al. [75]	MO				MTT
Bing [70]	MO				MM
Sinriech and Palni [59]	MO			CT	MC
Meersmans and Wagelmans [47]	MO				
Veeravalli et al. [66]	MO				
Sinriechy and Kotlarskiy [60]	MO				CT, WIP
Krishnamurthy et al. [37]		MO	SV	CD	MM
Ilić [31]		MO	MV	T	MDVE
Lee et al. [40]		MO			MTT
Rajotia et al. [53]		MO	SV	T	TW
Jawahar et al. [33]		MO		T	SPT, LPT, LTT, STT
Oboth et al. [10]		MO	MV	CD	VS, NV,D, MIAT
Desaulniers et al. [13]		MO	SV	-	MCD
Levitin and Abezgaouz [41]		MO	MV	-	MT, MS
Yoo et al. [74]		MO	MV	CD	MDA
Fazlollahtabar et al. [20]	S		MV	CD	

MO mathematic optimization; S simulation; MT meta-heuristic; AI artificial intelligence; FC facility demand; MV: multi-vehicle; SV: single-vehicle; CD customer demand; T travel/transport time; MTT minimize travel time; CL customer location; MC minimum completion time; CT Cycle time; WIP work in process; MM minimize makespan; MDVE minimize the distance the vehicle travels empty; TW time window; SPT shortest operation time; LPT longest operation time; LTT longest travel time; STT shortest travel time; VS vehicle speed; NV number of vehicles; D demand; MIAT minimize idle AGV travel; MCD minimize cost delay; MS minimize space; MDA deadlock avoidance; MIT machine idle time; MHTC material handling time and cost; MMW minimize maximum workload.

Based on the last researches, the research gaps identified are presented as follows:

According to Mehrabian el al. [48] the prediction during FMS production schemes falls far behind compared to the actul scheduling, thus in real-life problems parameters like due dates, demand, and completion time are always uncertain. Be that as it may, the study of uncertainty facility locations demands and demand quantity has not been seen in the earlier works. The research focused on a dynamic scheduling problem, where several machines and AGVs move with a stable speed on a shop floor [27].

Nowadays, these automated guided vehicles generally are mobile vehicles without drivers or robots that are used in transportation systems De Ryck et al. [12], Stopka [61]. Another research developed a non-linear integer mathematical programming model to group several machines into several rings to make an efficient configuration for the AGV system in Tandem layout. Avoid Air-Pollution: In container ports and industrial plants, ships, trucks, and other fossil fuel engines are the most important sources for the generation of air pollution in these environments. Using AGV in these environments can significantly reduce air pollution. Edrissi et al. [15] another research developed a distributed system of multi-agent to scheduling problems of the robotic flexible assembly cells [32]. Minimize total cost including pollution and routing costs and the second is to maximize supply reliability. Tirkolaee et al. [4] minimized total costs including pollution and routing costs and the second is to maximize supply reliability. Ghobadi et al. [23] presented a Multi-Depot Electric Vehicle Routing Problem (MD-EVRP) with recharging stations considering the fuzzy time windows in pickup/delivery. Ghobadi et al. [23] the application of an Electric Vehicle (EV), especially in various operations of goods transportation used a solution for salvaging the crowded cities of the world. Goli et al. [24] addressed the cell formation and inter-cellular scheduling problems in a CMS environment and formulated them as integrated problems. The literature review in the AGV scheduling production system is summarized in *Table 2*.

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3 | Problem Statement

The presented research focused on the AGV location routing operation models to minimize the cost of transportation of shops in the company. The problem was divided into two parts: one as the facility AGV allocation planning problem and the second integrated LRP problem of AGVs. The framework is based on a Mixed-Integer Programming (MIP) algorithm for dispatching candidate generation on both location routing and demand satisfaction in Facility Layout Problem (FLP) and assignment of AGVs. This MIP algorithm includes a powerful stochastic procedure. The problem is modeled first as an uncertainty sub-tour stochastic approach. It is possible to obtain an exact sub tour for facility job services and choosing the best location for AGVs despatching. Next, we decide to assign the AGVs to the facility by uncertainty demands. In the real world, the demand for jobs that request for AGVs is unknown. For example, some Trucking and load/unload operations have deference time depend on the type of demands, type of vehicles, and manpower skills. So we used to keep some AGVs idle and still on waiting until on related facility applied.

In intelligent location–routing we modeled the request AGV, path assignment, dispatching location, and occurs the uncertainty of demands together. So the presented model minimized the empty trip, total cost of dispatching opening, and transportation. What differentiates the solution values of the routine flow path network and those of the Intelligence AGV Location–Routing (IALRP) is said to be a good reference for a firm or organization looking for its distribution operations. *Fig. 1* and *Fig. 2* compares the solutions of the flow path network with its corresponding IALRP solution. *Fig. 1* illustrates an example of a flow path network solution with solid arcs, while *Fig. 2* represents the IALRP method including the uncertainty demands with unsolid arcs corresponding to machine demands case any robots must be move along the resist path to visit all facilities.

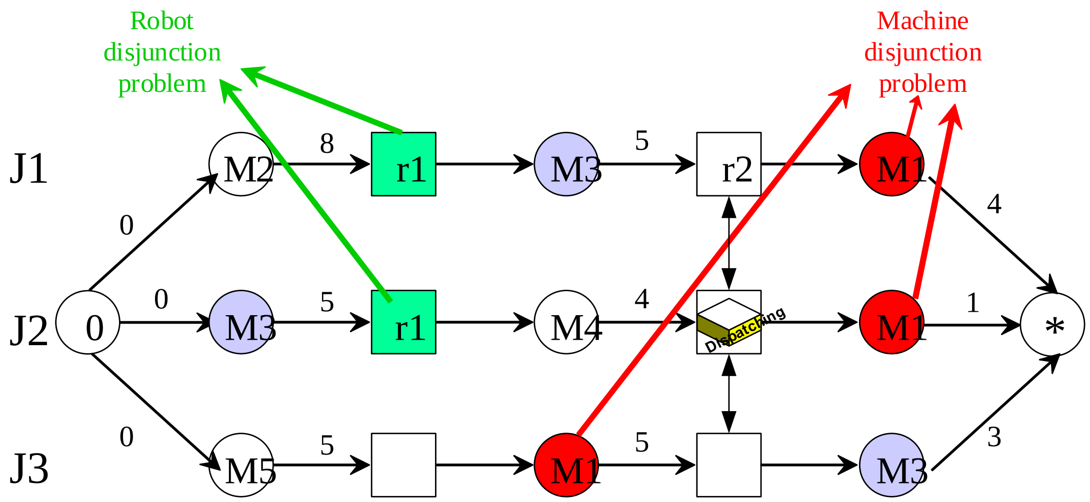

Fig. 1. Exact route dispatching location.

Egbelu et al. [16] focused on minimization of the maximum response time of the vehicle to movement empty from the dispatching depot to the facility point and even distribution of idle of vehicles over the network. *Fig. 3* represents the 3 jobs, 5 machines, and 3 robots in 3 shops, so according to the figure if the robots have exact demand with exact location, then idle time and the empty trip will be increased.

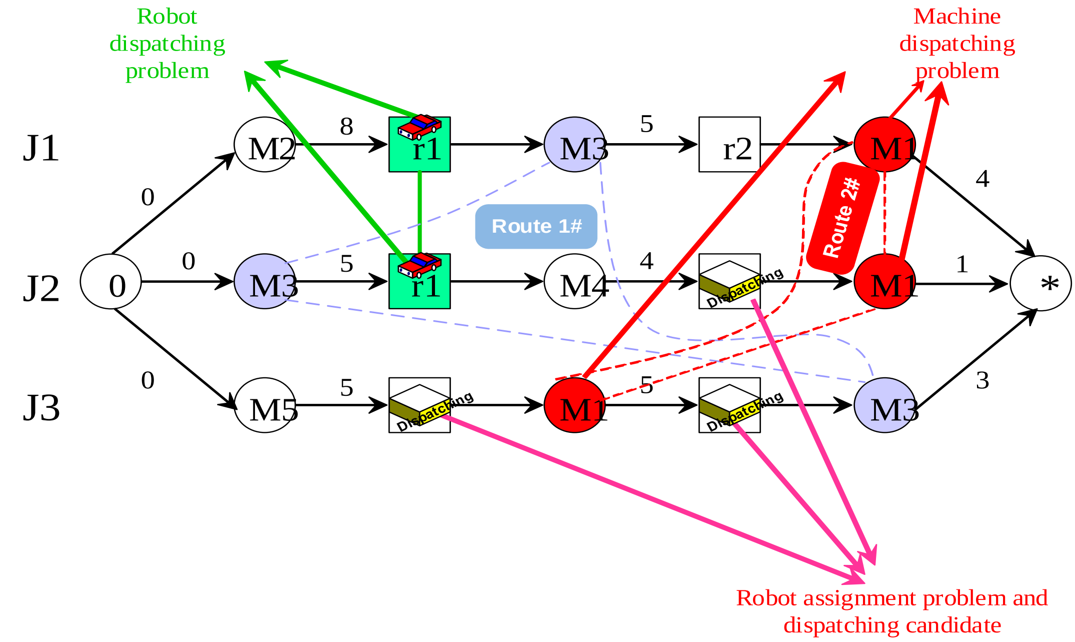

Fig. 2. An uncertainty demand route dispatching location.

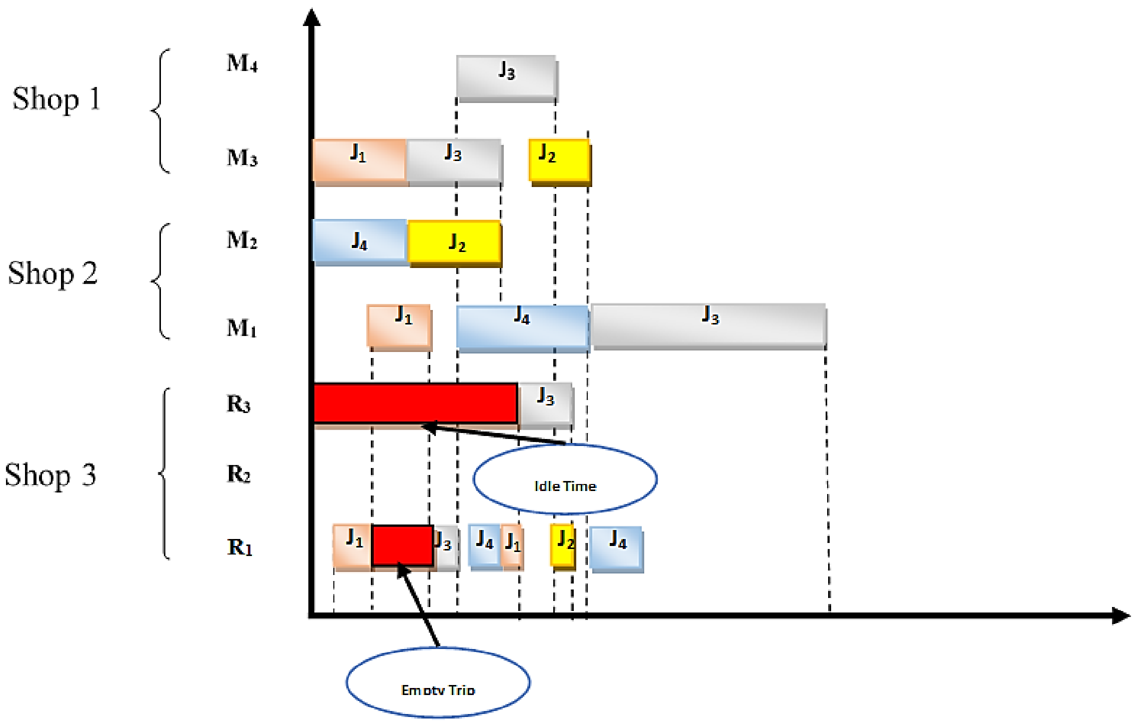

Fig. 3. Example of a solution with empty trip.

The main objective of the multi-facility ALRP is to reduce the total cost of the transportation system, such as dispatching opening costs and AGV trucking along the planning horizon.

Yang et al. [82] there are facilities' set with given demands and coordinates using sparsely distributed passive RFID tags for efficient object localization. However, the assumption used to determine the coordinates for facilities is relaxed in our study. In effect, the situation-based vulnerability sets are considered for facilities of different production. A known direction is additionally given with a set of candidates AGV dispatching, each being related to an opening cost. The total demands delivered to the facility location fitted the capacity of AGV's space. Each AGV is used to provide services to the facility so that to meet his demands. In effect, the total demand of the facility is assigned to an AGV according

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to AGV capacity. Finally, each AGV route is connected from dispatching as a starting point to a facility as an endpoint. The parameters and decision variables for a schematic example are shown in *Table 3*, *Table 4* and *Table 5*.

Table 1. Parameter definition.

Notation	Definition
b	Capacity of AGV.
a	The capacity of available AGV for products.
c	Costs.
u	Capacity of dispatching.
d	AGV's demand of dispatching for machines request.
k	The starting points (candidate for dispatching).
DC	The coordinate of demand.
i	Number of machines.
j	number of *AGV,s*.
h	Cost of dispatching service opening.
F	Stable node for production.
r	The number of available AGV assigned to the start points.
$\mathbf{f_{kj}}$	The location of demand corresponding to the paths.

Table 2. Notation definition.

Notation	Definition
x_{jip}	Quantity production type P from node i to control node.
x_{ikp}	Quantity production type P from node i to dispatching node.
x_{jkm}	Quantity production type m from node i to control node.
x_{jrm}	Quantity of product type m from AGV to warehouse r.
x_{kfm}	Quantity of product type m from dispatching to machine f.
x_{krm}	Quantity of product type m from dispatching to warehouse r.
$y_{jm} \in \{0,1\}$	Yij equals 1 if AGV from j is assigned to point i. According to the variable opening costs and demands.
$Q_{km} \in \{0,1\}$	Qkm equals 1 if AGV from dispatching k is assigned to product m.

Table 3. Multi-period AGV intelligence model parameters.

Notation	Definition
$\widetilde{D}_k$	The total intelligent capacity of start points.
$\widetilde{Sup}_s$	Location of AGV refer according to uncertainty demand.
$\widetilde{W}_j$	Facility demand.
d_i	Uncertainty capacity of go and round-trip route.
C_{ji}	Number of Facility location candidate with uncertainty demand.
a_{kj}	Type of facility capacity.
t_{sk}	AGV operators according to AGV point visited.
C_h	Facility location candidate capacity.
S	AGV capacity.

$$
\begin{aligned}
\text{Min } Z = & \sum_{j=1}^{J}\sum_{p=1}^{P} c_{jp}^{oc} Y_{jm} + \sum_{k=1}^{K}\sum_{m=1}^{M} c_{km}^{oc} Q_{km} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P} c_{ijp} x_{ijp} \\
& + \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{p=1}^{P} c_{ikp} x_{ikp} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{m=1}^{M} c_{jkm} x_{jkm} \\
& + \sum_{j=1}^{J}\sum_{r=1}^{R}\sum_{m=1}^{M} c_{jrm} x_{jrm} + \sum_{k=1}^{K}\sum_{f=1}^{F}\sum_{m=1}^{M} c_{kfm} x_{kfm} \\
& + \sum_{k=1}^{K}\sum_{r=1}^{R}\sum_{m=1}^{M} c_{krm} x_{krm} .
\end{aligned} \tag{1}
$$

s.t.

$$\sum_{j=1}^{J} x_{ijp} \le a_{ip}, \forall i, p. \tag{2}$$

$$\sum_{k=1}^{K} x_{ikp} \le a_{ip}, \forall i, p. \tag{3}$$

$$\sum_{k=1}^{K} x_{jkm} \le b_{jm} Y_{jm}, \forall j, p, m. \tag{4}$$

$$\sum_{r=1}^{R} x_{jrm} \le b_{jm} Y_{jm}, \forall j, p, m. \tag{5}$$

$$\sum_{f=1}^{F} x_{kfm} \le u_{km} Q_{km}, \forall k, m. \tag{6}$$

$$\sum_{r=1}^{R} x_{krm} \le u_{km} Q_{km}, \forall k, m. \tag{7}$$

$$\sum_{j=1}^{J}\sum_{k=1}^{K} x_{jkm} \le n_{mp} \left(\sum_{i=1}^{I}\sum_{j=1}^{J} x_{ijp} \right) \forall m, p. \tag{8}$$

$$\sum_{j=1}^{J}\sum_{r=1}^{R} x_{jrm} \le n_{mp} \left(\sum_{i=1}^{I}\sum_{j=1}^{J} x_{ijp} \right) \forall m, p. \tag{9}$$

$$P\left(\sum_{j=1}^{J}\sum_{k=1}^{K} x_{jkm} \ge \sum_{f=1}^{F} d_{fm} \right) \ge 1 - \alpha_{fm} \ \forall\ f, m. \tag{10}$$

$$P\left(\sum_{i=1}^{I}\sum_{k=1}^{K} x_{ikp} \ge \sum_{r=1}^{R} d_{rp} \right) \ge 1 - \alpha_{\ rp}, \forall r, p. \tag{11}$$

$$P\left(\sum_{k=1}^{K} x_{kfm} \ge d_{fm} \right) \ge 1 - \alpha_{\ fm}, \forall f, m. \tag{12}$$

$$P\left(\sum_{k=1}^{K} x_{krp} \ge d_{rp} \right) \ge 1 - \alpha_{rp}, \forall r, p. \tag{13}$$

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$$P\left(\sum_{j=1}^{J} x_{jrm} \geq d_{rm}\right) \geq 1-\alpha_{rm}, \forall r, m. \tag{14}$$

$$\sum_{j=1}^{J} Y_{jm} \leq J, \qquad \forall m. \tag{15}$$

$$\sum_{k=1}^{K} Q_{km} \leq K, \qquad \forall m. \tag{16}$$

$$x_{ijp}, x_{ikp}, x_{jkm}, x_{jrm}, x_{kfm}, x_{krm}, x_{jdm,} \geq 0, \forall\ i, j, k, r, f, p, m. \tag{17}$$

$$Y_{jm} = \{0,1\}\ \forall j, m. \tag{18}$$

$$Q_{km} = \{0,1\}\ \forall k, m. \tag{19}$$

The main objective (1) of this problem is to minimize the total cost, including the fixed cost of AGV transportation cost and the cost of dispatching/charge opening.

3.1 | Constraints

- ***Reverse depot capacity:*** *These Eqs. (2) and (3) mentions that the quantity of products output from machines to dispatching equal to or less than the capacity of machines.*
- ***Controlling capacity:*** *Eqs. (4) and (5) ensure that the parts of transport by AGV to dispatching are equal to or less than the capacity of AGV.*
- *Constraints (6) and (7) is the number of parts transported from dispatching (if it's open) to machines and warehouse must be equal or less than the capacity of dispatching.*
- ***Path balancing:*** *Eqs. (8) and (9) related to AGV parts follow balance with* n_{mp} *index.*
- ***Path Demand balancing:*** *The Constraints (10) and (11) mentions parts transported from machines and AGVs to dispatching are pulled demand systems.*
- *Constrain (12) shows the demand of machines for parts is random. Eq. (13) showed the demand for parts from the warehouse is random. Eq. (14) implies that the demand for warehouses is random.*
- ***Maximize depot opening****: Constraints (15) and (16) showed upper bound of dispatching allowed depot opening in uncertainty situation.*
- ***Binary constraints****: These constraints (17) and (18) and (19) are decision variables for point i, j.*

3.2 | Uncertainty AGVLRP Formulation

As mentioned above the uncertainty model applied to this problem so we used normal density function to change uncertainty model to a certainty model as follows:

$\mu,\sigma2$, $fx=12\pi\cdot\sigma e-x-\mu\sigma22$, $-\infty<x<+\infty$,

$$\text{So if } Z = \frac{x-\mu}{\sigma} \sim n(0,1) \Rightarrow \begin{cases} f(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2} \\ -\infty < z < +\infty \end{cases},$$

$P(Z > z_\alpha) = \alpha$, $P(Z < z_\alpha) = 1 - \alpha$.

For example, we suppose this uncertainty constraints such as $\sum_{j=1}^{n} X_j \leq K$ with normal distribution $K \sim n(\mu, \sigma^2)$ as $P(\sum_{j=1}^{n} X_j \leq K) \geq 1-\alpha$ equal to $P\left(\frac{K-\mu}{\sigma} > \frac{\sum_{j=1}^{n} X_j-\mu}{\sigma}\right) \geq 1-\alpha$ or $P\left(Z > \frac{\sum_{j=1}^{n} X_j-\mu}{\sigma}\right) \geq 1-\alpha$ as a result: $\frac{\sum_{j=1}^{n} X_j-\mu}{\sigma} \leq Z_{1-\alpha}$ or $\sum_{j=1}^{n} X_j \leq \sigma . Z_{1-\alpha} + \mu$.

3.3 | Problem Linear Optimization

The purposed chance constraint of the structure of a linear optimization problem is written by:

$$P\left(\sum_{j=1}^{n} X_j \leq K\right) \geq 1-\alpha \approx \sum_{j=1}^{n} X_j \leq \sigma . Z_{1-\alpha} + \mu. \tag{20}$$

With the usage of *Eq. (20)* we can change uncertainty normal constraint to an exact constraint.

4 | Proposed Approach

Exactly in the absence of likelihood information, the undefined parameters, the ordinary rate, and diverse objectives as in Section 4 are inconsequential. Various healthiness measures are being suggested for this condition. There are two typical measures; SP and chance constraint, which are not movable concerning one another as discussed in Sections 4.1 and 4.2.

4.1 | Overview of Approaches

Stochastic AGV Location Routing Problem (SALRP) is also a generic name given to ALRP that considers one or more unknown or stochastic parameters during problem modelling. The SALRP presents a type of problem that combines the stochastic parameters and Integer Programs (IP) and is often regarded as NP-hard models. The random parameters may be the presence of location machine or facility, the several customer's demands at an exact location, the time such as service or delivery time, pick up time, or transportation time. Berman et al. [6] present a single mobile service centre for customer dispatching demand the contact server demand created a queue with stochastic parameters. SP as a research area to find broad coverage of mathematical properties, models, and solution algorithms Birge and Louveaux [7] and the uncertainty parameter has known distribution. Zahan et al. [76] used artificial bone manufacturing and a stochastic optimization model to help disease in elderly people. Dhingra et al. [14] and The Continuous-Time Markov Chain (CTMC) applied to achieve scheduling and planning of AGVs, combined the solution of a two-level with a stochastic model, it proved that the shipping container handling time was affected by AGVs path. Also, Mishra et al. [50] and [63] applied the stochastic queue to solve Inter-Terminal Transportation (ITT) and applied the model to Port of Rotterdam. Shao et al. [57] applied a multi-stage traffic control strategy to resolve trade-offs and problems in AGV systems. A traffic control system is used to operate each motion AGV after utilizing an A∗ algorithm to the optimum path set for AGVs.

4.2 | Proposed Algorithm

The major steps of the proposed algorithm are shown in *Fig. 4*. However, the detail of the same is well explained in the next section. In Step 1, create random locations according to Lu et al. [44] and Yang et al. [73] real instance. In Step 2, calculate a rectangular distance between facility locations and AGV's. In Step 3, assign dispatching depot selection to AGV's and AGV's to facilities assignment. In Step 4, calculate the cost minimization and find a feasible solution (e.g., routing).

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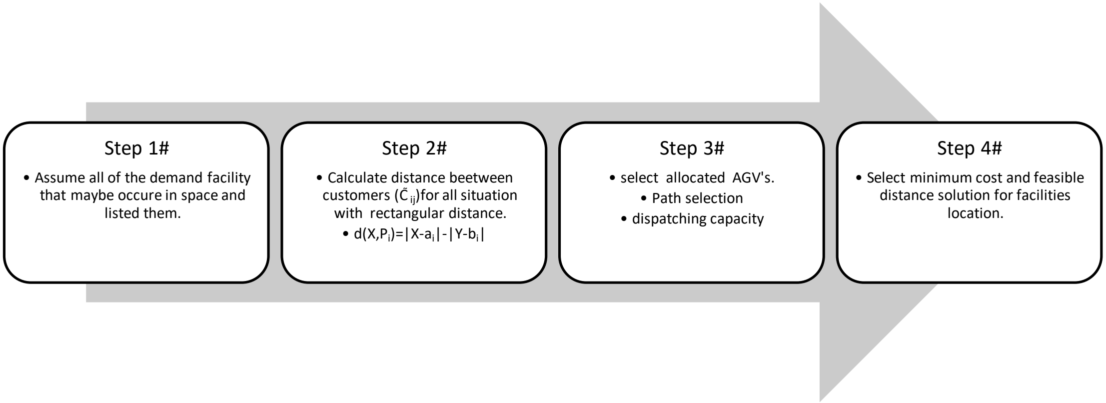

Fig. 4. Steps of the proposed algorithm.

For rearranging the portrayal of the arrangement, it is accepted that there is a model with 32 facilities and 5 main nodes with 2 periods of time. *Table 6* shows the answer to this issue. Obviously, in this arrangement, a priority requirement between the facilities of every depot is considered. For taking care of this issue, this arrangement requires a heuristic strategy. In this strategy, horizontal and vertical stochastic radii of every ellipsoid are characterized as $2t$ times and select the best stop to benefit them. After that, we select the best visit for the cost objective function minimization.

Table 6. Example of 5 facilities and 2 periods.

Available Facility	5	1	2	4	3
Period	1	2	3	4	5
Available Depot-d	1	2	5	3	4
Customers-n	1	2	3	4	5

The string of number display sequence covers the location of dispatching depots, how facilities are allocated to AGV's and the route between them. For example facility number 5 visits the first one and net 1, 2, 4, and 5.

4.3 | Constraint Satisfaction

Constraints on observing the sequence and avoiding creating a sub-loop are automatically satisfied depending on the type of answer string definition. Cause the simulation process of the system is very convenient, starting from the point where you start the workstation/dispatching to the first node and then back to the next node (transport path) and finally back to the supply point. We do this process for each period. In the same process, all variables in the model are updated. The most important variable is the value sent to each node.

Given the type of answer string definition that the numbers are binary $\in \{0,1\}$, a normalization is first performed on these numbers, which sum to one after which the share of each node is multiplied by the percentage in the answer string multiplied by the total volume of the AGV. The entire volume of the AGV is emptied to the end and returned to the supply point. After specifying this variable according to the relationship in the model presented in section three, easily calculate the number of AGV carrying the number of AGV by type and capacity of the transport routes, the number of transport purposes of the facility in terms of demand calculate in uncertainty demand.

4.4 | Imperialist Competitive Algorithm and Variable Neighbourhood Search (ICAVNS)

Therefore, the initial number of colonies for an emperor is calculated by:

$$NC_n = \text{round}\{p_n.N_{col}\}. \tag{24}$$

Where, NC_n - original number of colonies for the nth emperor, while N_{col} - the overall number of colonies. NC_n, the number of colonies is randomly selected and assigned to each emperor. This way, an emperor with greater strength will have a higher number of colonies than a weaker emperor.

4.4.2 | Total strength of an emperor

The total strength of an emperor is subjective to the strength of the emperor's country. Nonetheless, the strength of the colonies for an emperor will influence the total strength of that emperor. Hence, the total strength of an emperor can be calculated by:

$$\text{TP Emp}_n = (\text{Total Cost}(\text{imperialist}_n) + \xi\text{mean}\{\text{Total Cost}(\text{colonies of empire} \quad)\}s).$$

Where *TP Emp*$_n$ represents the total strength of the *n*-th emperor, while ξ is a positive number less than 1. Thus, we create *pop1* which is the primary population.

4.4.3 | Imperialist colonies move toward the emperor

Having been allocated, the colonies moved toward their emperors. This move is illustrated in *Fig. 5*, where d represents the distance between the colony and the emperor. X shows a random variable with a uniform distribution between $d\in\beta$ and zero, while $\beta > 1$. The direction has been shown as an angle (θ). Moreover, P_A displays the rate of solutions approximating toward the emperor.

4.4.4 | Transfer of information between colonies

The information between the colonies is transferred through a crossover operator in the genetic algorithm. For the crossover operator, one-point and two-point crossovers are employed. Tournament selection is used to select the colonies. Moreover, P_c represented the percentage of solutions subject to the crossover. The continuous crossover applied in this model *Fig. 6*.

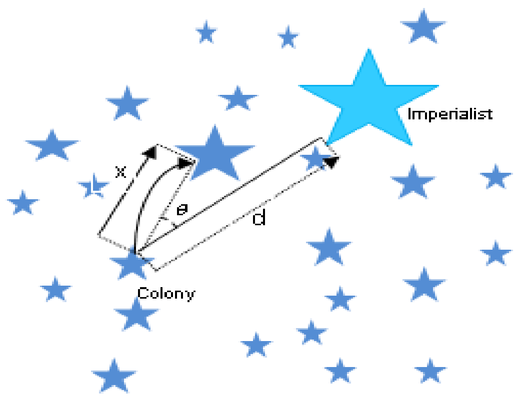

Fig. 5. Colonies move toward the emperors at a random angle.

Illustrated a schematic shape of a sample method display. In this method, a random vector is generated between 0 and 1, and the second random vector is complementary to this initial vector. Thereafter, two children are generated according to the following formula:

$$
\begin{aligned}
&R_1 \square \mathrm{Rand},\\
&R_2 = 1 - R_1,\\
&O_1 = P_1 * R_1 + P_2 * R_2,\\
&O_2 = P_1 * R_2 + P_2 * R_1.
\end{aligned}
$$

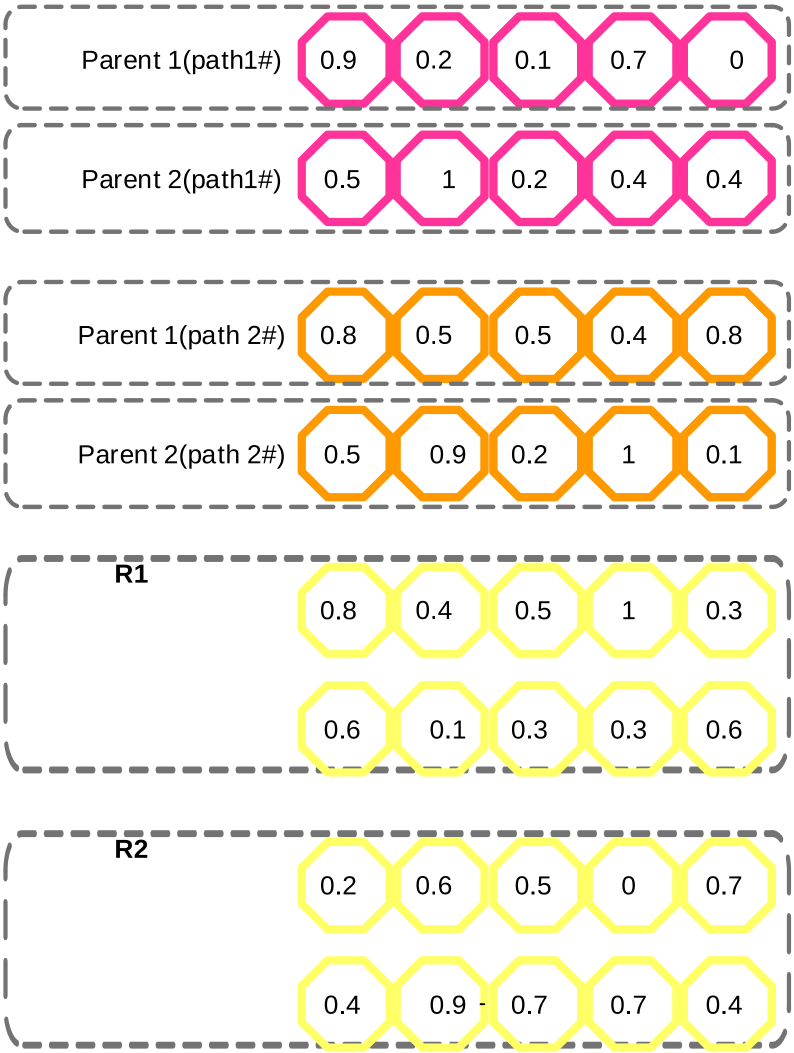

Fig. 6. Continuous crossover.

The random selection operator is used for path parent selection also the elitism Reddy and Rao [55] method applied for randomly gen place chosen for replacement.

The stopping condition for ending the imperialist competition takes place when there is only one emperor left from all the countries as illustrated in the pseudo code of the hybrid ICAVNS method (see *Fig. 7*).

Begin

Initialization %

– Set Parameters ((MaxIt, PopSize), n_d, nd_i, nc_i, t, cd_k, fd_k)

– Generating initial countries (Pop1)

– Evaluaute fitness value of Pop1

Position shift between colonies%

For it = 1 to MaxIt do

- Colonies attraction by an empire of the imperialist

→ Select random individuals position: (X_1, X_2);

Choice one scenario for assimilation operation(Pop2);

Revolution beetwen colonies and imperialist%

→Use VNS as a local search for reach to better imperialists;

Update colonies%

If cost of countries < imperialist result

- replacement related colony positions instead of imperialist and

end

Imperialistic competition %

– Total power of empires is Calculated

– choice and assign the worst colony of the weakest empire to

one of the power empires issue on their costs

– delete the weakness empires (the imperialist empty of colony)

Merge%

Combined all of population {Pop1 ∪ Pop2 ∪ Pop3};

Choice n_{pop} country according to affinity function;

end for

Output : Extract the best solution with minimum cost function;

end.

Fig. 7. ICAVNS pseudo code.

5 | Experimental Evaluation

These arrangements have a place in the best transformative arrangement. Also, the arithmetic tests are performed to assess the adequacy and effectiveness of the arrangement depicted. To compare the solution methods for this model, we give a prime example to compare the results of the methods together. In this case the number of periods equal to 4, the number of nodes (transport routes) equal to 5, the number of automobiles transported by type and capacity of the transport routes, the number of transport purposes of the facility in the conditions of initial demand uncertainty. At each node equal to 5,000, the exact location of demand per unit of time equals 10, the number of starting points equals 100, the number of supply points, and at the same time intelligent management centers for automated vehicles equal to 5 and the weight of each sub-function. Equals 0.1. The rest of the parameter values are as follows.

Table 7 Shows the distance of five nodes between the exact demands points specified the capacity of path demand in an uncertain situation. Any point has 5 situations in path demand and namely, we have 25 conditions. Corresponding to 5 nodes the capacity of any facility demand showed in *Table 8*. We have 9 paths (scenario) with 6 samples in 5 iteration level leads to the position of demand showed in *Table 9*.

Table 7. Volume and capacity of path demand and distance between exact demand point.

	i1	i2	i3	i4	i5
i1	0	54.20332	49.49747	56.0803	55
i2	54.20332	0	34.05877	2.236068	6.708204
i3	49.49747	34.05877	0	36.01389	40.31129
i4	56.0803	2.236068	36.01389	0	5.656854
i5	55	6.708204	40.31129	5.656854	0

Table 8. Capacity of facility.

	i1	i2	i3	i4	i5
capacity	21.9545	74.02702	61.18823	76.05919	75.69016

Table 9. The exact location of demand.

	t1	t2	t3	t4
i1	44	56	80	38
i2	13	19	87	93
i3	39	93	21	87
i4	31	36	23	49
i5	54	15	48	60

Corresponding to 5 transportation paths, we have 25 quantity levels of paths that lead to demand locations. The tolerance of chance limit implies in *Table 10*.

Table 10. Various facility demands.

	t1	t2	t3	t4
i1	73	73	73	73
i2	34	34	34	34
i3	25	25	25	25
i4	89	89	89	89
i5	19	19	19	19

The quantity demand in 4 periods with 5 nodes showed in *Table 11*.

Table 11. Work period matrix.

	t1	t2	t3	t4
i1	51	51	51	51
i2	75	75	75	75
i3	4	4	4	4
i4	56	56	56	56
i5	91	91	91	91

The main test problem was solved by the suggestion algorithm and compared with the optimization package used as the LP and integer programming. The best results outcome for 78^{day} is 18341058 that implies validity and good convexity according to the exact algorithm solution.

5.1 | Parameters Setting

Taguchi's arrangement of the trial named the TDOE procedure helps researchers tune the best parameter before the operation is created. In effect, a definite figure for simulating the desirable data is presented by reducing the number of simulations. It is significantly extraordinary to regulate reactions influenced by different elements. The Taguchi technique joins the affirmation of a wide unit of test conditions, outlined as orthogonal exhibits, to decrease slip-ups and overhaul the proficiency and repeatability of the examinations. Orthogonal arrays are a set of numbers developed to skilfully achieve ideal test plans by thinking about various exploratory circumstances. The Taguchi strategy, then again, utilizes motion to-commotion proportion, false name SNR rather than the normal incentive to interpret the information into an incentive for a trademark, which is being assessed inside the ideal setting investigation. The utilization SNR is because it shows both the variety of the quality trademark and the normal value.

Initial design parameters table as shown in *Table 12*. There are 4 parameters in three-level. It also considers the intersection action at three levels, which represents the percentage of intersections at defined levels. Then, using the ICAVNS algorithm, we investigate different scenarios for designing a multi-objective AGV routing model in terms of demand uncertainty by considering demand uncertainty in the number of vehicles based on the type and capacity of the transport routes. We address the number of transportation facilities in terms of demand uncertainty. To design an AGV routing model as a multi-objective problem under demand uncertainty, we examined three iteration levels, 1 to 10 nodes per iteration, and 25 to 150 population units. While there are many standard orthogonal arrays available, each of the arrays is meant for a specific number of independent design variables and levels. As an example, if one wants to experiment to understand the influence of 4 different independent variables with each variable having 3 set values, then an L9 (*Table 13*) instead of 3^4=81experiment and orthogonal array might be the right choice.

Table 12. Orthogonal array.

Parameters	A	B	C	D
Level	No. nodes	No. paths	N_{pop}	$N_{iteration}$
Low (1)	2	1	25	100
Medium (2)	3	5	75	300
High (3)	4	10	150	700

Table 13. Problem scenario setting.

Scenario	No. nodes	No. paths	N pop	N iteration
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

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5.2 | Computational Evaluation

5.2.1 | Small-scale problem

In this section, the operation of ICAVNS metaheuristic was measured and the respective deterministic solutions are given. The exact experiments are then executed in a PC having a processor of 2.6 GHz and a RAM of 16 GB with GAMS®. *Table 14* shows the results of the stochastic location problem.

Table 14. Results of small scale.

No.	Number of Paths	Number of Periods	ICAVNS Obj	ICAVNS Time
1	2	2	33999997	98
2	2	4	68201853	157
3	3	7	110326067	180
4	3	11	247363446	251
5	4	2	483921596	602
6	4	6	692231026	1224
7	5	9	965224129	2651
8	7	17	1289524523	5974
9	12	24	1530603628	8680
10	15	32	2170865465	10080

We show that by increasing the periods and increasing the number of nodes to 15 nodes, the target function has increased from 33999997 units to 2170865465. In other words, with increasing demand volume and scope, task status and type of facility control, and the number of facilities based on total points of origin and supply points in the main nodes, the precise demand-generating location has increased non-linear against linear increasing.

Nine scenarios with six examples and five iterations were created for any experiment. The following are *Tables 15* and *16*. Of the objective function obtained, the order of the working seasons and the nodes (source routes) of the precise location of demand generation based on intelligent capacity, the number of transport facilities in terms of demand uncertainty, and the RPD.

In each test run the value of the objective function obtained shall be following the Taguchi method relative to the order of the working seasons and the nodes of origin to evaluate the exact location of demand generation based on intelligent capacity, number of transport facilities in uncertainty. The demand, which is a variable response, is converted and analyzed according to its changes. In the Taguchi method with goal maximization, the S/N ratio is the ratio of the variable that the objective function in each execution converts to that ratio to decide according to the following equation.

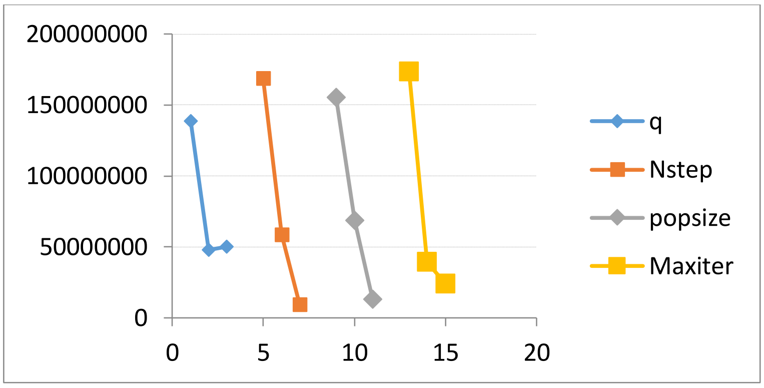
$$S/N_1 = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right). \tag{27}$$

The results of the implementation of the algorithms are shown in the tables which show the quality of the algorithm's performance. And *Eq. (28)* shows how to calculate the RPD value M_i is the value of the objective function obtained for each algorithm implementation M_{min} is the lowest value of the objective function obtained for solving each of the three algorithms.

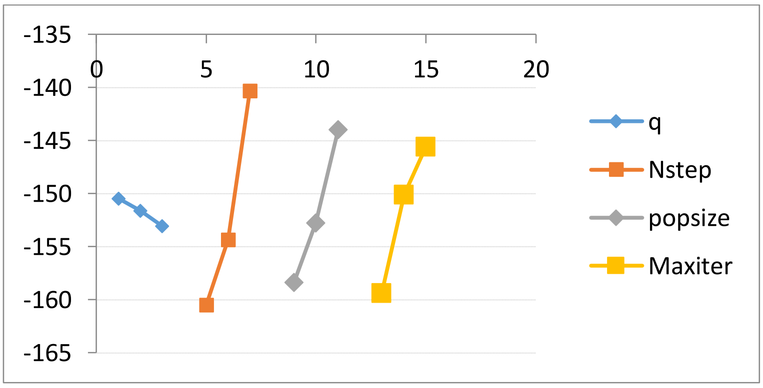
$$\text{Relative percentage deviation (RPD)} = \frac{M_i - M_{min}}{M_{min}}. \tag{28}$$

According to the diagrams obtained in Taguchi's method, the 1th level of crossover percentage parameter is selected, 2th level for node percentile parameter, 3th level for population parameter, and 4th level is selected for iteration parameter.

Fig. 9 shows the normal S/N and its proportions. The ideal levels are A(2), B(1), C(3), D(3). Thus, the results processed in terms of minimizing the mean of the maximum total cost in the Taguchi exploratory investigation affirmed the ideal levels utilizing the S/N ratio (see *Fig. 8*). *Table 16* shows the results of uncertainty demand in 20 paths for the AVG location routing problem.



a



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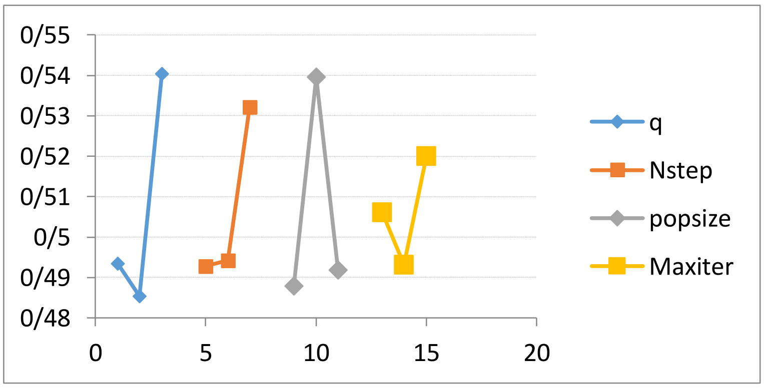

c

Fig. 8. Taguchi method showing the S/N ratio plot: a. objective; b. seasons period paths and nodes; c. performance tolerance.

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Table 16. RPD results from the ICAVNS algorithm.

	Mean RPD	0.46	0.45	0.57	0.47	0.51	0.48	0.55	0.52	0.55
	Iteration	**road1**	**road2**	**road3**	**road4**	**road5**	**road6**	**road7**	**road8**	**road9**
Sample 1	1	1	0.22	0.86	0.53	0	0.84	0.62	0.37	1
	2	0.11	0	0	0.29	0.51	0.52	0.92	1	0
	3	0.45	0.58	1	1	0.9	0.87	0.85	0.01	0.99
	4	0	0.55	0.11	0.32	1	0	0	0	0.13
	5	0.21	1	0.7	0	0.55	1	1	0.47	0
Sample 2	1	0	0.59	0.81	0.51	0.49	1	1	0	0.91
	2	0.53	0.49	0.94	0	0	0.04	0.33	1	0.66
	3	1	0	0	1	1	0.69	0.72	0.76	1
	4	0.23	1	1	0.01	0.9	0	0.43	0.84	0
	5	0.84	0.74	0.65	0.47	0.27	0.77	0	0.31	0.85
Sample 3	1	0.12	0	0.91	0	0.91	0.39	0.26	0.92	0.76
	2	0.74	1	1	0.25	0.48	1	0.59	0.4	0
	3	0.06	0.4	0.25	0.06	0	0.63	0	1	0.85
	4	0	0.05	0.81	0.02	1	0	0.49	0.7	0.27
	5	1	0.17	0	1	0.02	0.55	1	0	1
Sample 4	1	0.25	1	0.91	0.42	0.82	1	0	0.2	0.52
	2	0	0.2	0	1	0.04	0	1	0.99	0
	3	1	0	1	0.91	0.06	0.23	0.88	0	0.77
	4	0.5	0.19	0.26	0.58	0	0.37	0.73	1	0.26
	5	0.16	0.04	0.03	0	1	0.2	0.68	0.09	1
Sample 5	1	0.82	0.55	0.3	0.51	0.99	0.47	0.43	0	0
	2	0.89	0.52	0.32	0.36	1	0.18	0.06	0.73	0.88
	3	0.8	1	1	0	0.33	0	1	0.77	0.4
	4	0	0	0.9	0.55	0	1	0.03	0.32	1
	5	1	0.52	0	1	0.37	0.33	0	1	0.84
Sample 6	1	0.34	0	0.76	0.87	0	0.13	0	0.1	0
	2	1	0.83	1	0.61	0.66	1	1	0	0.51
	3	0	0.54	0.84	0	1	0.92	0.82	0.9	0.19
	4	0.26	0.58	0	1	0.12	0.74	0.53	1	1
	5	0.52	1	0.62	0.81	0.74	0	0.91	0.87	0.723

Based on the proposed algorithm and considering Gams software, a general framework of the proposed path that constitutes our model can be examined. In these 20 paths, we have provided two outputs to solve the route problems: One the first output (considering the exact location of the demand), and the second output (taking into account a small level of work). In both outputs, the values of each path are explained by specified criteria. Examination of the first 20 paths for the first output can show that the first path and the eighteenth path have the highest index level and show the best response. Examination of the first 20 paths for the second output can show that the first and third paths and the eighteenth path have the highest index level and show the best results in *Table 17*.

Table 17. The final value of dispatching system corresponding to facility and dispatching point.

dispatching path	rework/rejected product	No dispatching center equal to facility demand called	time of periods	First Objective result	second Objective result	Point value 2	Point value 2
1x	10	12	7	34	7	1	1
2x	10	17	5	6	1	0.169	0.169
3x	15	25	3	10	10	1	1
4x	12	14	4	2	5	0.581	0.576
5x	11	13	5	29	8	0.954	0.948
6x	12	14	2	7	2	0.127	0.12
7x	15	12	5	39	4	0.975	0.975
8x	12	14	7	6	4	0.4	0.4
9x	9	9	5	2	10	0.664	0.664
10x	11	10	4	7	6	0.541	0.541
11x	9	19	7	1	4	0.11	0.11
12x	17	15	5	0	6	0.493	0.493
13x	11	10	6	10	6	0.419	0.419
14x	10	17	8	20	9	0.534	0.534
15x	12	14	9	5	4	0.4	0.4
16x	9	9	2	7	6	0.9	0.9
17x	11	10	9	2	3	0.175	0.175
18x	12	14	5	14	10	1	1
19x	14	15	7	9	7	0.92	0.92
20x	12	14	4	5	3	0.349	0.312

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