Emergency Resource Storage Facility Location Problem Considering Domino Effect After an Earthquake

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To the Almighty

To my family

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ABSTRACT

In the case of natural disasters, the sufferings of affected people know no bounds. The earth is facing challenges to work for the survival of human being as life become endangered during disasters. Sometimes one natural disaster leads to another disaster, which is termed as a domino effect in the natural disaster. These incidents make the life of people vulnerable who are living in risk zones of a probable disaster incident. Earthquakes of big magnitude can be followed by other disastrous incidents like fire accidents, floods, tsunami, etc. The demand for emergency resources increases due to the domino effect. Organizations associated with making decisions regarding helping the suffered people should try to take necessary steps, which may include storing emergency resources to assist the disaster-affected people. To my knowledge, no previous studies were focusing to store emergency resources for helping people affected by the domino effect in natural disasters. This thesis work tries to give light to this scenario. The probability of domino effect due to natural disaster is calculated at first then with that result along with other necessary data, the location of facilities and the amount of emergency resources at optimum cost has been determined.

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CHAPTER 1

INTRODUCTION

Facility location is to select the optimal place for facilities to conduct a firms' operation. Determining the geographic site of facilities is a critical decision that should be taken strategically. Humanitarian logistics deals with warehousing supplies and organizing delivery to the affected people in the case of any disasters [1]. Resource forecasting and optimization, inventory management, information exchange are needed to be decided in humanitarian logistics and this is the process of planning, implementing, and controlling an efficient cost-effective flow and storage of relief to provide to the suffering people [1]. There are many losses during any disaster. These losses may include different infrastructures, roads, millions of lives, etc. which put the people in a very vulnerable state. There arises scarcity of food, water, medicine during these times. Organization's personnel need to plan on inventory management, infrastructure, information technology, and transportation to build up a well-developed humanitarian logistics network [2]. In this process, there include three flows- flow of material, the flow of money, and the flow of information [3]. The main objective of humanitarian logistics is to minimize losses where demand is highly variable and inventory management is so much challenging [4]. Loss can be minimized by responding to sudden incidents promptly. Different studies indicated that, for having a successful emergency distribution management and reducing damage to human beings, identification of actual demand of relief for the affected people, arranging required items, and the distribution of reliefs promptly are the main important things [5].

The effects of pre-disaster and post-disaster relief funding on the relief system's performance had been analyzed by integrating facility location and inventory decisions [6]. A maximal covering type model was developed here for determining the number and locations of distribution centers and the number of relief supplies to be stocked at each distribution. Enough inventory should be stored in distribution centers for satisfying demand and disasters may not happen at a time; these were the assumptions used in this model.

If an accident in one-unit spreads to nearby units, this can be characterized as a domino effect or chain of accidents [7]. Here first accident is considered as a primary event that triggers other accidents in nearby units and the overall consequence is more severe than the primary event. This domino effect can also be observed in natural disasters when one disaster can lead to another disaster.

At the time of the domino effect, the damage of materials, equipment, industrial systems, environment, etc. may lead to injury of people. This is the concept for escalation.

Domino effect may have three following features [8] :

a. Primary accidental scenario initiating domino accident sequence;
b. The primary event generates physical effects for which escalation vectors propagate primary scenario which may result in the damage of a minimum of one secondary target;
c. One or more secondary accident situations or events involving the same or different installation units favors the propagation of the primary events.

Natural, human and technological can be potential sources of domino effects [9].

- The natural origin of the domino effect can be climate origins such as forest fire, floods, storms, tornadoes, or geological origin such as earthquakes, tsunamis, eruptions from volcanos, etc.
- Human origins include human failure, defect in design or sabotage, theft, revenge actions, etc.
- Technological origin can be pool fire, flash fire, explosion, toxic chemical release, etc.

These risks can be compounded which makes the analysis complex enough leading to the exploitation of different analysis methods like deterministic, stochastic, and quantitative methods.

These potential sources, initiating event and immediate environment are directly related to the propagation process.

1.1 Rationale of the Study

With the changing global environment, we are facing disasters almost every year. People suffer much in these cases because many of them lose shelters, find no food or drink. They need support from others.

Faults of rock at a shallow or deeper depth of earth can propagate seismic waves resulting in sudden motion or trembling in the earth's crust which is known as an earthquake. The accumulated energy released by an earthquake is equivalent to or larger than the energy released by the atomic bomb which leads to devastating damages. Earthquake waves can collapse structures resulting in death and injury of human beings and damage to properties. Short circuit and gas explosion due to the movement of ground can initiate fire hazard creating post-earthquake threat which may lead to the domino effect.

So far, few papers have addressed the domino effect in natural disaster scenarios. If an earthquake leads to the domino effect, it is important to determine emergency resource storage facility locations to provide support to the affected people. Taking these factors into account, considering the domino effect in the determination of locations of emergency facilities is an open problem and constitutes the scope of the present work.

1.2 Objectives of the Study

a) To formulate a model for determining the location of facilities to store emergency resources if an earthquake leads to the domino effect.
b) To optimize total cost which includes facility setup and operating cost as fixed cost, and transportation cost. And also optimize unutilized capacity.
c) To determine the amount of storage of emergency resources to be stored at each facility.
d) To develop a numerical hypothetical example of the problem for a better understanding of the model.

The result of this work will be helpful to determine facility location when an earthquake faces a domino effect and a mixed-integer linear programming model will optimize total cost and unutilized capacity.

1.3 Outline of the Methodology

The proposed research methodology is outlined below:

i) Earthquake is considered here as the primary incident. The secondary incidents which can occur due to primary incident have been found from literature.
ii) The total area of the map is divided into grids. From these grid points, candidate facility locations and demand areas are selected.

iii) Demand is calculated from the population of demand areas and probabilities of occurrence of the primary incident and secondary incidents have been used to determine the final demand.

iv) Probabilities of occurrence of the primary incidents and secondary incidents are estimated from domino functions.

v) Distance between candidate facility locations and demand areas is determined using suitable software. QGIS software is used for this.

vi) To determine the location of facilities by minimizing total cost and to determine the amount of storage of emergency resources, a mixed-integer linear optimization model is used and solved using suitable software. Python is chosen for this.

vii) The methodologies are illustrated for an example problem.

CHAPTER 2
LITERATURE REVIEW

Different facility models have been developed to respond to the disaster-affected people. Bangladesh is a disaster-prone country. In Bangladesh, floods and tropical cyclones are considered major natural disasters. The geographical location of Bangladesh makes this country risky to the probable danger of earthquake disaster that can lead to building collapse and many human lives will be threatened for this. Most of the buildings of Bangladesh are not strong enough to endure a big or medium size earthquake. So, if any such earthquake occurs, it will collapse the buildings as well as take lives, and if a domino effect occurs then people will require so many reliefs.

Domino effect can be considered as a chain or series of accidents and here an accident propagates to other accidents. Damage probability or domino effect frequency estimation has been focused on the study of domino effects [7]. Damage probability is also known as escalation probability and can be estimated using different models. The probit model is a popular model for determining escalation probability because of its' simplicity and flexibility [10]. After developing escalation probability, it is then used to estimate the probability of the domino effect for that case.

To study and analyze domino effects, the main existing methodologies and software tools had been identified in a review paper [11]. Lees defined the domino effect as a factor taking into account the hazards if escalation of any incident occurs due to the leakage of a hazardous material [12]. He gave another definition, where he defined domino accident as an event whose consequences cause separate event in a separate unit [13]. Others defined domino effect as an accidental event in which a primary event propagates to nearby equipment by triggering secondary events which would make the overall consequence more severe [14]. During the development of the domino effect, the process which promotes the degradation of property and injury to people is called escalation. So, in the industrial field, any event spreads from equipment or industrial unit can be classified as a domino event [11]. Domino accident is initiated by a primary accidental scenario and due to an escalation vector primary event is propagated resulting in damage of at least one secondary target and the secondary event then propagates the primary event. From that paper it can be known the classification of domino event initiation which are – natural origins such as climate and geological, human origins such as organizational and intentional, technological origin such as fire, explosion, or toxic release. Most of the models which analyzed domino effects due to fire and overpressure use the probit model, which was discussed here. They also discussed different types of methods and software tools that have been developed to analyze domino effects in industrial sites, such as domino effect analysis (DEA) methodology, quantitative assessment of risk caused by domino effect, assessing domino effects based on Monte Carlo simulation, etc.

A recent methodology built on Bayesian Networks has been introduced for probabilistic analysis of domino effects in the plants that are processing chemicals [7]. Here Bayesian Network was formed for the propagation pattern of the domino effect starting from an initial event. The field of risk analysis and reliability engineering under uncertainty have been using Bayesian Network and this is a probabilistic graphical method [15]. This network forms a flexible graphical structure showing relationships among the nodes of the network and the strength of the relationships is determined by assigning conditional probabilities to the nodes and Bayes Theorem is used to update the probabilities. The joint probability distribution of the events leading to the domino effect is derived here by developing the propagation pattern of the domino effect as a Bayesian Network and after calculating the probability of the primary event and the conditional probabilities of other events [7]. It is assumed here that the primary event or starting point is X_1, and the sequential order of the events are $X_1 \rightarrow X_3 \rightarrow X_2/X_4 \rightarrow X_5/X_6$ then the joint probability distribution of the events leading to domino effect U = {X_1, ..., X_6}is expressed and calculated using this equation [7]:

$$P(U) = P(X_1)P(X_3|X_1)P(X_2|X_1, X_3)P(X_4|X_1, X_3)P(X_5|X_2, X_3)P(X_6|X_3, X_4)$$

After that domino effect probability is calculated by multiplying two probabilities; the probability of primary event and escalation probability.

A mathematical model for estimating the probability of domino effect in parallel pipelines has been developed [16]. They considered hole location, jet direction, the diameter of pipelines, and the distance between them. They proposed a probability model for one-dimensional jet impingement where jet issuing from source pipe impinges on target pipe and these pipes are separated by a distance. The result of the model shows the probability of domino effect on target pipe increases with decreasing distance between both pipes and as the diameter of the target pipe increases and the diameter of the source pipe decreases. The probability of target pipe failure is estimated with a simplified approach. The evaluation of probability for thermal radiation is not treated here. Domino effect frequency is estimated here by the rate of occurrence of initial release from the source pipe and the probability of damage to the target pipe. So, when installing parallel pipelines, the possibility of a loss in one of them affecting the others should be taken into consideration which is important for risk management. The main limitations here were considering one-dimensional jet and this can be applicable for parallel pipelines not crossing pipes.

For the estimation of escalation thresholds and escalation probabilities which can be triggered by fire scenarios, a simplified approach was developed [17]. They obtained a simplified model to estimate the time to failure of a storage vessel concerning the radiation intensity on the vessel shell and a multi-level approach was used under different fire conditions. A finite element model was developed to allow a detailed simulation of the radiation mode, wall temperature, and stress over the vessel shell. A time-lapse exists between the primary event and secondary events caused by escalation as storage vessel failure is a slow process of wall heating up. The authors of this paper determined that the escalation threshold values are strongly dependent on vessel category and the maximum time required for effective mitigation. A specific probit function was used here relating time to failure to the probability of escalation,

$$\mathrm{Pr} = a + b\ln(ttf)$$

Pr is the probit variable, ttf is the time to failure in absence of mitigation action, and the coefficients of the probit function a and b may be derived by comparing time to failure and time to effective mitigation. They apply the model to case-studies and allow the assessment of the increase in the individual risk for domino scenarios which may contribute to industrial risk.

A systematic procedure was developed for the quantitative assessment of risk caused by the domino effect and the result proved that to correctly assess and control risk caused by the domino effect, it is important to include quantitative analysis of the domino effect in quantitative area risk analysis [8]. For assessing the vulnerability and consequence of domino scenarios, a simplified technique was introduced here. They considered first-level domino effects where the further escalation of secondary events was not included and the escalation vector was limited to radiation, overpressure, and fragment projection. To the comparative assessment of the case studies, the individual risk, societal risk, and potential life loss were calculated in each case for the primary event and domino scenarios. The results point out that it is important to consider domino effect quantitative analysis in the quantitative risk analysis framework for emergency response and planning concerning with possible domino scenarios.

Dhaka did not have a big earthquake in the last 100 years and records show that Bangladesh experienced a big earthquake before 100 years [18]. Human lives and households are damaged by earthquakes. So, Bangladesh is in a vulnerable zone for earthquakes. From this report, we can know that Dhaka has been placed among the 20 most vulnerable cities in the world according to the earthquake disaster risk index. There are three major fault lines which make the country more vulnerable to earthquake. These fault lines are – Madhupur fault, Dauki fault, and Eastern Plate Boundary fault. Five tectonic blocks of Bangladesh and the neighborhood can produce damaging earthquakes. They are – Bogra fault zone, Tripura fault zone, Sub Dauki fault zone, Shillong fault zone, Assam fault zone [19].

Before the implementation of the building code, most of the buildings had been built in Bangladesh making the buildings very poor strength to withstand a small earthquake [18]. So, enhancing the safety and quality of buildings are so much necessary for Bangladesh.

Earthquakes have the capability of damaging structures and infrastructure systems leading to threat to life, property, and the economy of a country. The following Figure: 2.1 shows the occurrence of the earthquakes of different magnitudes around Bangladesh and the different fault lines can also be seen here [20].

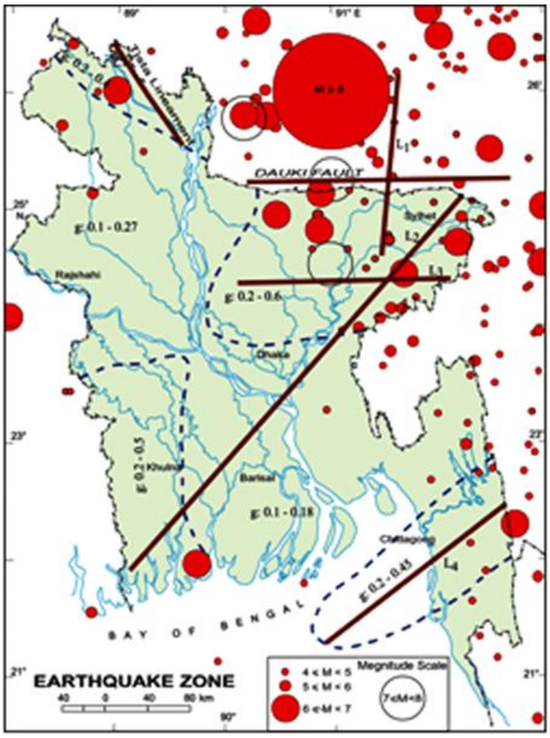


Fig. 2. 1: Earthquake occurrences around Bangladesh as per magnitude [21]

Earthquake-prone regions in the historical past and the expectation of occurring earthquake in future is expressed by seismic zone. Frequent earthquake-faced regions have high seismicity than regions facing a small and less frequent earthquake. Bangladesh has been divided into three seismic zones – zone I, zone II and zone III [22]. The most active zone for earthquakes is zone I which is the high-risk zone, zone II is a moderate risk zone and zone III is a seismically quiet zone. This seismic zonation has been done based on earthquake epicenters and morphotectonic behavior of tectonic blocks of Bangladesh rather than the ground conditions.

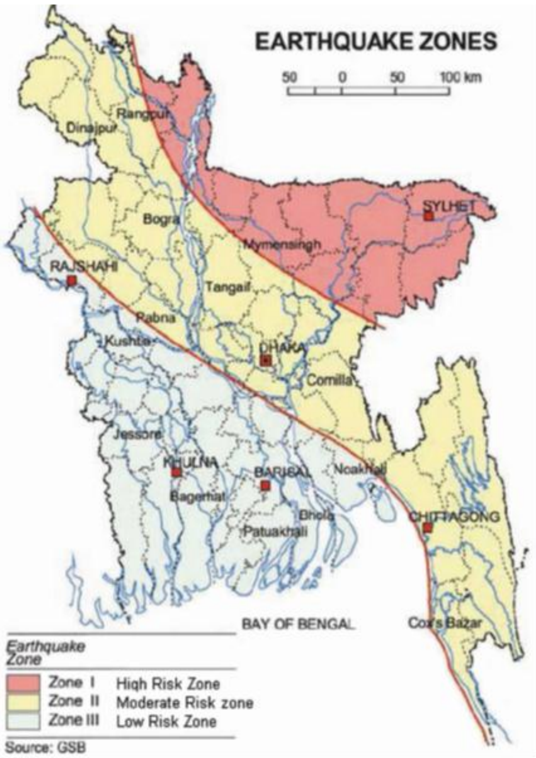


Fig. 2. 2: Seismic zoning map of Bangladesh [22]

Seismic hazard of different parts of Bangladesh has been highlighted in the following Figure: 2.3.

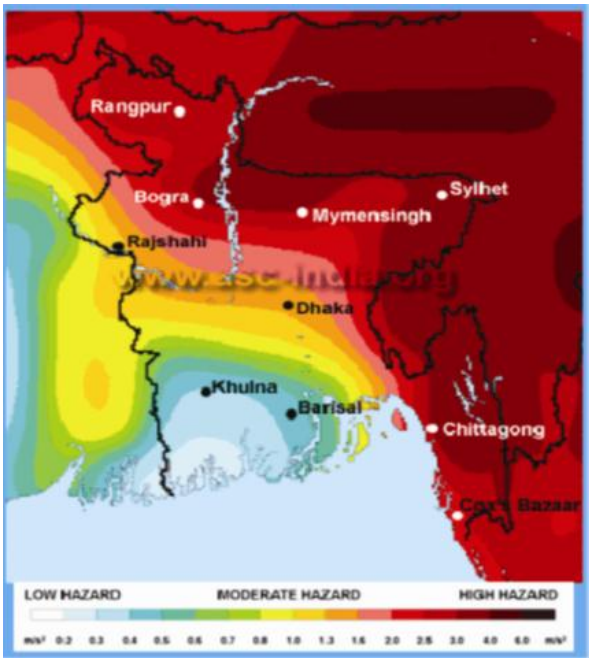


Fig. 2. 3: Earthquake risk in Bangladesh [23]

An Earthquake may accelerate accidental scenarios by releasing hazardous materials. A specific approach was developed to assess natural-technological (NaTech) risk as a result of accidental scenarios triggering by earthquakes [24]. How accidental scenarios initiated by earthquakes contribute to the overall industrial risk were assessed by three case studies by the authors. The methodology can be applied to analyze the impact on industrial systems including hazardous materials when an external hazard occurs. Results from case studies showed that potential life loss which is the average expected frequency of fatalities as a result of accidental events in the target area increase by at least one order of magnitude due to earthquakes in process and chemical plants. So, the results here proved that external events like earthquakes may be a significant contributor to overall industrial risk in the process and chemical plants. Pressurized tanks and even if atmospheric storage tanks were more critical equipment shown in their result. So, while assessing industrial risk due to the impact of earthquakes, multiple damage states of the process equipment should be considered by risk analysts.

To assess local and social risk indicators as a result of earthquake-leading accidents, a specific approach had been developed allowing identification and assessment of all possible scenarios due to the earthquake [25]. Here it is indicated that a linear correlation is present between the probit variable and the dose which is an independent variable of the log-normal distribution –

$$\mathrm{Pr} = a + b\ln(dose)$$

A GIS-based risk recomposition software had been used for implementing the method to allow the calculation of individual and social risk lined to industrial accidents. To represent the actual scenario of the seismic hazard of the site, the authors used convolution of the derivative of the seismic hazard curve along with the equipment fragility curve. To consider the interaction between natural and technological hazards when planning for using land is an important issue.

Bayesian network and coupling effects are taken into consideration to analyze the domino effect of pool fire in the storage areas of the petrochemical industry [26]. The propagation patterns of the domino effect and occurrence probability of domino accidents at the first and second levels are obtained here. It has been shown here that, pool fire occurring at only one tank does not affect any tank at far away but for multiple thermal radiation fields, the increasing trend is noticed for the occurrence possibility of domino accident and during pool fire cooling of the adjacent tank can prevent domino accident. Here, the escalation probability of atmospheric and pressure vessels affected by thermal radiation had been estimated using Probit models. They determined that if the safety distance between tanks is a minimum of 31.17m, then the produced thermal radiation flux does not cause a domino accident.

To describe the damage phenomenon under overpressure, a detailed class of damage state, as well as loss intensity was applied and a reasonable assignment of damage probability was made in a model [27]. In quantitative risk analysis, damage probability and the relative threshold value are considered as two necessary parameters. Here authors developed reliable probit models for specific categories of chemical process equipment. They gave evidence against the improvements of present models by comparing them with other models in the literature. Probit analysis had been used at first as a model to assess dose-effect relationship for human response against thermal radiation, toxic substance, and overpressure, and damage probability can be assessed through this analysis and the equation used for this,

$$Y = a + b\ln(\Delta P)$$

where Y is the probit value, ΔP is peak static overpressure (Pa), a and b are coefficients of the model [28].

To assess risk caused by the domino effect in industrial sites, specific escalation criteria for primary scenarios were obtained and revised threshold values were proposed in a paper [29]. They considered three escalation vectors – radiation, overpressure, and fragment projection to obtain threshold criteria. Here it is shown that, if Y is the probit function, ttf is the time to failure (sec), V is the vessel volume (m^3), and I is the amount of heat radiation received by the target vessel (kW/m^2); then for atmospheric vessel threshold value is 15 kW/m^2 and Y = 12.54 – 1.847 $\times \ln(ttf)$ and $\ln(ttf) = -1.128 \times \ln(I) - 2.667 \times 10^{-5}V$. Their approach may represent a starting point for the quantitative assessment of the domino effect. The authors suggested future research to consider immediate actions of thermal radiation and flame impingement as well as additional stresses and impulses to assess near field effects of fire and explosion.

The importance to use equipment-specific models for determining damage probability and equipment-specific damage threshold values had been analyzed in a paper [10]. The authors revised available data on damage to process equipment for quantitative assessment of domino effects as a result of overpressure. For several categories of process equipment, they derived specific probit models. Their study focused on the assessment and further development of a stochastic overpressure damage model to process equipment within domino effect analysis. Modification of proposed models for the assessment of damage to the equipment of the process in the perspective of quantitative risk analysis suggested the use of probit models for damage correlation data. Probit models derived from the analysis of available data can be directly used to assess the potential damage to the equipment due to blast waves. The authors said that, for twenty percentage the expected probability of damage distance is 500 m lower for pressurized vessels against atmospheric vessels and different threshold values should be used for different equipment categories.

A methodology based on stochastic models and physical equations for evaluating the risk of domino effects on industrial sites due to heat load and over pressuring waves had been presented in a paper [9]. Their results provided a proof for the significance of domino effect assessment within risk analysis by allowing to quantify the effect of escalation vector in industrial plants to choose safe distances between industrial equipment with the definition of three areas – zone of certain destruction, zone of possible destruction, and safety zone. After evaluating the probability of domino sequence for all systems, failure probability for each subsystem can be evaluated with this method. They assumed the primary scenario can cause the rupture of one tank which generates three escalation vectors – heat radiation, overpressure, and fragments affecting surrounding equipment. The authors considered heat radiation and overpressure in this paper for simplification. As heat load and overpressure can affect the environment and people, so to estimate the individual and societal risk, a human vulnerability model can be developed further.

Probit (probability estimate) equation for modeling of the release of gas or materials is described as in this equation:

$$Y = k_1 + k_2 \ln V$$

where probit function Y is the percentage of the population who may be affected by the release of fire or any other incidents, k_1 and k_2 are constants, V is the magnitude of effect which may depend on the magnitude and duration of the event [30]. This equation shows that as the volume of events increases, the percentage of affected people increases by a small amount.

To prevent the domino effect-based disaster, a prediction method had been proposed [31]. This method can assess the probability of a domino effect at different levels if lightning strikes the chemical storage tanks. By using the event tree method, they analyzed causes of fire, and a probability calculation model had been developed if a fire accident had been triggered by lightning. They demonstrated the accident chain graph by considering multi-level domino effects and calculated the probability of each accident chain with the application of the Bayesian network. By comparing the probabilities of the domino effect at different levels, primary equipment that would be most dangerous and the most sensible target equipment had been identified by setting failure states for different tanks. The authors justified the method with two case studies in a chemical tank farm. Here probit model is used to calculate the escalation probability of target equipment and after the calculation of probit function Y, the escalation probability can be obtained with this formula [29] :

$$P_E = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{Y-5} e^{\frac{-u^2}{2}} du$$

Determining the optimal location for facilities is one of the decisions that organizations should have to make technically and there are various methods for obtaining this decision most of which are deterministic which may not project real-world scenarios accurately. To build a model considering the uncertainty of demand for different periods, there was research where stochastic constrain programming had been used which converted the stochastic model to deterministic [32]. The authors implemented the model for a case study and using MATLAB software examined the efficiency of the model. The model can help better management when the status of the facility changes. Minimizing cost for the changes in facility operation states and transferring demand which is stochastic from facilities to customers considering Euclidean distance between them was the objective of that study. They implemented the model for a dairy factory and considered discreet uniform distribution for customers' demand. They calculated total cost for different facilities status such as – not existing facility, open facility, closed facility, reopen facility over a planning horizon and also calculated average demand in each period, the average cost in different scenarios, and average all facilities status. The following formula was used for their objective function (here i is the number of customers, j is the number of facilities, t is planning horizons):

$$\min \sum_{j=1}^{n} \sum_{t=1}^{T} (\textit{opening cost of facility } j$$
$$\times \textit{ if facility } j \textit{ is installed at beginning of period } t \textit{ or not}$$
$$+ \textit{ holding cost of facility of } j \times \textit{ if facility } j \textit{ is avialble in period } t \textit{ or not}$$
$$+ \textit{ reopening cost of facility } j$$
$$\times \textit{ if facility is } j \textit{ reopened at beginning of period } t \textit{ or not}$$
$$+ \textit{ temporarily closing cost of facility } j$$
$$\times \textit{ if facility } j \textit{ is closed at beginning of period } t \textit{ or not}$$
$$+ \sum_{\textit{number of studied scenarios}} \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{t=1}^{T} \textit{function of number of studied scenarios}$$
$$\times \textit{ demand of customer } i \textit{ in period } t$$
$$\times \textit{ cost of supplying customer demand } i \textit{ from facility } j \textit{ in period } t$$
$$\times \textit{ if demand of customer } i \textit{ in period } t \textit{ supplied from facility } j \textit{ or not})$$

Dynamic demand capacitated location problem for multi-period when facilities are allowed to be relocated in each period and are kept at a fixed location had been considered in a paper [33]. Obtaining optimal locations of capacitated facilities to meet demand at minimum total cost including transportation cost, facility operating, opening and closing cost for all periods were the subjects of their interest. They also considered without relocation of facilities. Mixed-integer programming formulation, Lagrangian relaxation, and Benders Decomposition algorithms had been used here. The authors considered total demand following increasing, decreasing, or steady patterns and changes in demand distribution to evaluate the performance of the algorithm. The authors randomly generate customer locations and then from a discrete uniform distribution, each customer demand is randomly generated for each period. During the planning horizon, changing of location and level of demand were their assumption. They also randomly generated the capacity of each facility. A base capacity had been determined. If p is expected open facilities as a percentage of total possible locations m and demand is D, then base capacity $Q = \left\lfloor \frac{D}{pm} \right\rfloor$. From this value, capacity is randomly generated from a uniform distribution $U[0.8Q, 1.2Q]$. They also randomly generated fixed operating costs from a discrete uniform distribution and fixed opening and closing costs from a uniform distribution. Cost structures, facilities capacity, and customer demand variation influence the efficiency of the solution algorithms. Benders Decomposition and Lagrangian relaxation algorithms proved to be more efficient than the branch and cut approach. Future studies can consider multi-stage location problems by varying demand and cost structures with time.

Balcik and Beamon considered their model by integrating facility location with inventory decisions for a humanitarian relief chain [6]. They developed a model to determine the number and locations of distribution centers and the amount of relief supplies to be stocked. They also considered pre-disaster and post-disaster costs.

Another paper focused on the source of provider-side uncertainty in humanitarian logistics and proposed a model for plant location problems using the genetic algorithm [34].

A review paper focused on data modeling types and problem types related to emergency humanitarian logistics [35].

From the recent studies, to the best of our knowledge, there was no study which focused domino effect after an earthquake to consider the location of emergency resource facilities. For this reason, this paper will try to have a light on such a scenario.

CHAPTER 3
MODEL DEVELOPMENT

3.1 Problem Identification

Researchers have already done so many researches on humanitarian logistics. For selecting cost-effective locations, different models have been developed. But there are some new ideas which were not addressed before.

Disasters may have a domino effect which means one disaster can lead to another disaster. The domino effect of disasters and humanitarian logistics both were researched separately, not in an integrated manner.

So, in this thesis, the aforementioned gap is addressed.

3.2 Problem Statement and Assumptions

This work is related to humanitarian logistics when the domino effect is under consideration. For the domino effect, an earthquake is considered as a primary incident that may lead to secondary incidents – building collapse and fire. Humans do not know when and how this will happen. So, the probability of primary incident and the probability of domino effect can be considered to optimize the resources in facilities. Facilities are for supplying relief to the disaster-affected people. This work is dedicated to select facilities that will minimize total cost while considering demand, transportation cost, storage cost, the capacity of facility, and probability of domino effect, and the probability of a primary incident. Some assumptions are made about the situation–

- Demand is deterministic and based on the population census
- The capacity of facilities is predefined
- Probit coefficients which are used for determining escalation probability, are taken as per assumption

3.3 Model Development

If an earthquake is considered as the first incident or primary event, this may sometimes lead to a domino effect such as building collapse and then fire.

3.3.1 Calculation of probability of domino effect

The probability of the domino effect can be calculated by multiplying the probability of the primary event and the escalation probability [7]. That is -

Probability of domino effect = Probability of primary event × Escalation probability

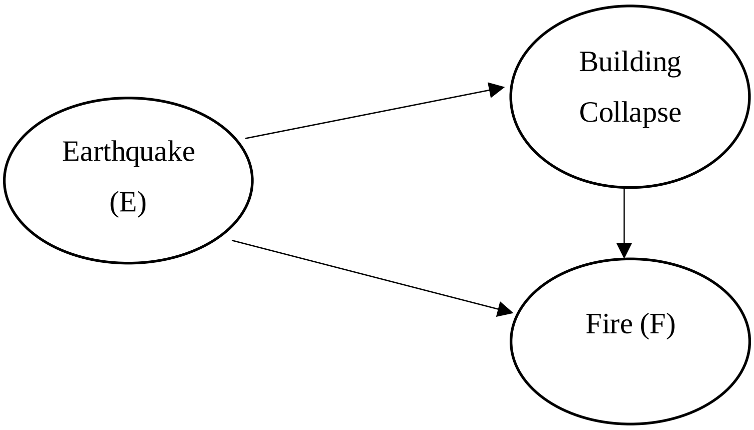


Fig. 3. 1: Domino Effect

3.3.2 Calculation of probability of escalation

The escalation probability can be calculated using the probit model. The word 'probit' is a linguistic blend of two words – **prob**ability + un**it**. The objective of this model is estimating probability where an observation having special features would fall into a specific category. A probability function called 'probit function' (Y) is used to relate damage to the factors responsible for the domino effect after the primary event [8].

$$Y = K_1 + K_2 \ln(factors) \qquad \text{......... (3.1)}$$

Here, Y is the probit for damage, and K_1 and K_2 are probit coefficients. After Y is calculated, the escalation probability can be [8],

$$P_E = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{Y-5} e^{\frac{-x^2}{2}} dx \qquad \text{......... (3.2)}$$

It is observed that, the escalation probability P_E remains 1 for the values of $K_1 = -1$ and $K_2 = 5$; $K_1 = -2$ and $K_2 = 4$; $K_1 = -3.5$ and $K_2 = 4.5$. If $K_1 = -5$ and $K_2 = 1.5$, the escalation probability is 0.29 and the probability of domino effect is 0.203. For $K_1 = -5$ and $K_2 = 0.5$, the probabilities become very small. These calculations are included in **Appendix A**. After trial and error, it is assumed that probit coefficients can be taken as $K_1 = -5$ and $K_2 = 1.5$. So,

$$Y = -5 + 1.5 \ln(factors) \qquad \text{......... (3.3)}$$

Here,

$$\ln(factors) = \ln\begin{pmatrix} number\ of\ building\ per\ square\ kilometer\ and \\ a\ constant \\ indicating\ absence\ or\ presence\ of \\ gas\ line\ or\ industry\ or\ hilly\ or\ coastal\ area \end{pmatrix} \quad \ldots (3.4)$$

3.3.3 Objective function and constraints

This work is a mixed-integer linear optimization problem. This is a multi-objective optimization problem and weighted sum method has been applied to solve the problem. Here two cases have been considered. Case I is without adding a constraint on the number of facilities to be set up. And Case II is adding a constraint on the number of facilities to be set up.

Case I:

The objective function of the problem will be,

$$\min \quad w_1\left(\sum_{i=1}^{n} F_i X_i + \sum_{i=1}^{n}\sum_{j=1}^{m} C_{ij}\, f_{ij}\right) + \ (1 - w_1)\ \left(\sum_{i=1}^{n} capacity_i X_i - \sum_{i=1}^{n}\sum_{j=1}^{m} f_{ij}\right) S_i \quad \ldots\ldots. (3.5)$$

Subject to:

$$\sum_i f_{ij} \ = \ (P_{j(1)} + \ P_{j(domino)})d_j \quad \forall j \quad \ldots\ldots\ldots. (3.6)$$

$$\sum_j f_{ij} \le capacity_i X_i \quad \forall i \quad \ldots\ldots\ldots. (3.7)$$

$$f_{ij} \ge 0 \qquad \forall i,j \quad \ldots\ldots\ldots. (3.8)$$

$$X_i = \{0,1\} \quad \forall i \quad \ldots\ldots\ldots. (3.9)$$

$$for\ \max(P_{j(domino)})\ , X_i = 0 \quad \ldots\ldots\ldots. (3.10)$$

Objective function:

(3.5) is the objective function of this problem. This consists of two parts. Cost part and unutilized capacity part. Fixed cost and transportation cost are the cost part. Weightage w_1 has been given to the cost part and weightage $(1 - w_1)$ has been given to the unutilized capacity after transferring demand. As it is two objective multi-optimization problem, so while one weightage is w_1, another one can be $(1 - w_1)$. The objective is to minimize both cost part and unutilized capacity part.

Meaning of the symbols:

w_1 is weightage to the cost part

$(1 - w_1)$ is weightage to the unutilized capacity part

i represents facility

j represents the demand area

n represents the total number of candidate facilities

m represents the total number of demand areas

F_i is a fixed cost for facility i

C_{ij} is transportation cost from facility i to demand area j which is considered as,

$$C_{ij} = Cost\ for\ transferring\ demand\ f_{ij}\ per\ km \times distance_{ij} \quad \ldots\ldots (3.11)$$

$P_{j(1)}$ is the probability of incident 1 at demand area j

$P_{j(domino)}$ is the probability of domino effect at demand area j

$\max(P_{j(domino)})$ is the maximum probability of domino effect at demand area j

f_{ij} is demand transferred from facility i to demand area j

d_j is demand at demand area j

$capacity_i$ is capacity for facility i

S_i is multiplication factor for unutilized capacity so that the effect of the unutilized capacity could not be negligible.

Decision variables:

X_i (which facility locations will be chosen, binary)

f_{ij} (how much demand will be transferred from facility i to demand area j)

Constraints:

(3.6) Demand for a demand area will be fulfilled from different facilities by transferring the different amounts of demand. The transferred amount will be equal to the summation of the probability of primary incident and probability of domino effect multiplied by demand of that area.

(3.7) Transferred demand amount from a facility will be less than or equal to the capacity of that facility. And if any facility will not be chosen, then the transferred demand amount from that facility will be zero.

(3.8) Transferred amount of demand will not be negative.

(3.9) Binary decision variable for facility location.

(3.10) When the probability of domino effect is maximum among these candidate locations, it is assumed here that no facility would be chosen for that location. As high domino effect probability can also affect facilities, so, it would be better to skip that location.

<u>Case II:</u>

In case II, everything will be same like Case I, just adding a constraint for number of facilities. It is considered here that; maximum number of facilities will be 3.

$\sum_i X_i \leq 3$ ……. (3.12)

Constraint (3.12) indicates that, maximum 3 facilities can be set up.

3.3.4 Selection of software for solving the problem

The problem is solved using the Python programming language. The Integrated Development Environment (IDE) used for this is PyCharm. It is developed by the company JetBrains. The version used for PyCharm is PyCharm Community Edition 2020.3.1. An integrated development environment is used to build applications combining common developers' tools into a single graphical user interface. As the manual configuration of multiple utilities is not necessary and integrated as part of the setup process, new applications can be started quickly for starting any program. This can speed up the workflows by intelligent code completion and automated code generation which saves time. So PyCharm is suitable for solving this problem and PyCharm Community Edition is an open-source version of PyCharm. Anaconda which is a free Python distribution has also been used to set up the packages for PyCharm. The version is Anaconda3 2020.11. Anaconda aims to make the management of the package simple. Most popular Python packages for science, engineering, math, and data analysis have been included in Anaconda. This helps to install packages. Gurobi optimizer which is an optimization solver has been used here. The version is Gurobi 9.1.1. This solver is widely used in linear programming, mixed-integer linear programming, quadratic programming, etc.

To determine distances between facilities and demand areas, a geographic information system (GIS) software is used. All types of geographic and spatial data (represents location, size, and shape of an object on earth) can be analyzed and stored, retrieved, managed, and displayed with GIS software. This software can analyze and present geographic information by producing maps and other graphic displays. QGIS (version 3.4) software is used here.

To obtain coordinates for determining distances, Google Earth Pro Software is used. At Google Earth Pro, the grid option should be on and by adding placemarks, longitude and latitude are obtained. The coordinates for the candidate facility locations are chosen from the center of the grid.

The objective is to select facility locations so that both cost and unutilized capacities are optimized by fulfilling demand. The possible amount of storing resources is also determined. This is done by applying both Gurobi solver and genetic algorithm.

CHAPTER 4
GENETIC ALGORITHM

4.1 Genetic Algorithm

A genetic algorithm is a metaheuristic algorithm built on the process of natural selection to generate high-quality solutions in optimization. This search heuristic is inspired by Charles Darwin's theory of natural evolution. In 1960, John Holland introduced genetic algorithms, and afterward, his student David E. Goldberg extended the algorithm in 1989 [36]. In a natural evolution, every species searchs for suitable adaptations in a changing and challenging environment. Each species tries to survive in the living world by changing the chromosome combinations. Charles Darwin's theory pointed out that the individuals which are 'fittest' are more prone to survive and have more probability to pass their good genes to successive generations, so this is 'survival of the fittest entities'.

A genetic algorithm starts with an initial population which is a set of random solutions. Each solution in the population is identified as a chromosome. The objective function of the problem is considered as the fitness function. Each chromosome is evaluated based on performance concerning the objective function. Better performance chromosomes are more likely to survive. By successive iterations which are called generations, chromosomes are evolved. During each generation, the chromosomes are evaluated and the fitter the chromosomes, the higher the probabilities of being selected for crossover and mutation. Crossover and mutation are genetic operations wherein the crossover, for generating an offspring which speeds the process to reach a better solution, two-parent chromosomes exchange portions of them. For avoiding trapping in a local optimum, diversity in the population is maintained in the mutation phase. After these two operations, according to the fitness value, some parents and some offspring are selected to form a new generation and the population size is constant by rejecting others. If the number of generations is predetermined, after completing the generations, the algorithm provides a near-optimal or optimal solution of the given problem by converging to the best fitness valued chromosome.

The operation procedure of the genetic algorithm has been depicted in Figure 4.1.

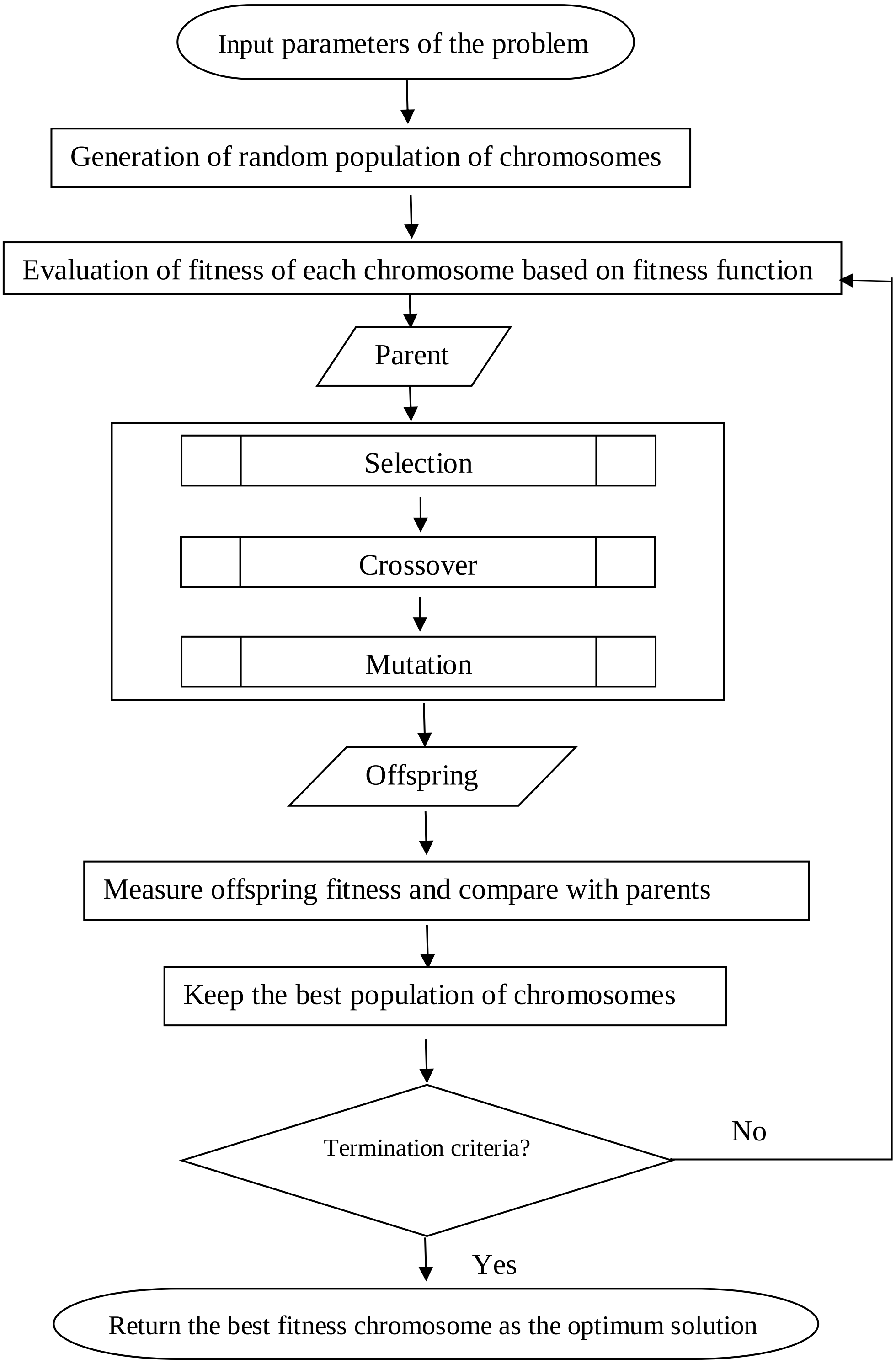


Fig. 4. 1: Flowchart of the Genetic Algorithm's working procedure [37]

So, five phases are considered in a genetic algorithm:

a) Initial population

b) Fitness function

c) Selection

d) Crossover

e) Mutation.

4.2 Operation Procedure of Genetic Algorithm to Solve the Emergency Resource Storage Facility Location Problem Considering Domino Effect after an Earthquake

The key elements of the genetic algorithms are gene, chromosome, and population. A set of variables which is called genes form a string of chromosomes. Chromosome represents a possible solution to the problem. A set of chromosomes or individuals forms a population. Chromosomes will represent which facility will be chosen for operation and which will not be chosen and this will be denoted with 0 or 1 values of each gene. 1 bit will be used for the opening of facility and 0 otherwise. Population size will be 30 and generation size will be 50 with the consideration of time and objective value. Chromosome length will denote facility count which is here 9. Gene, chromosome, and population are illustrated in figure 4.2.

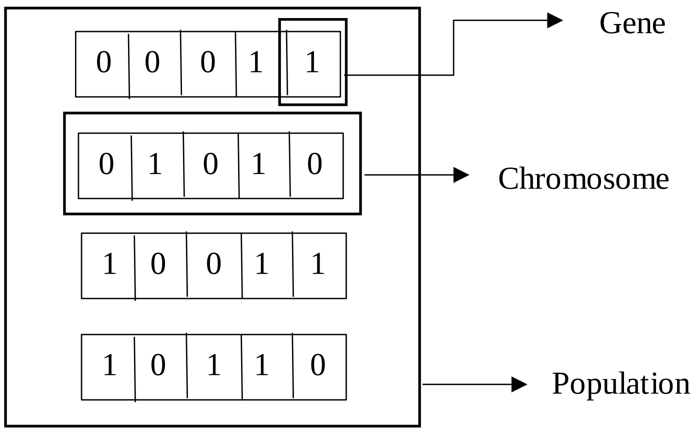


Fig. 4. 2: Population, chromosome, and gene of a genetic algorithm

For initialization, a random population is generated. For example, 30 chromosomes will be created with a length of 9 where each gene will denote the open status of facilities. During the generation of each solution (chromosome), the constraints are checked. If the solution satisfies the constraints then it returns the generated solution or generates another solution. The fitness function is used to evaluate the fitness of each solution of the population. The fitness value helps to determine better individuals which will be used in the next generations.

According to fitness, parent chromosomes are selected. High fitness of individuals helps them to select as parents for reproduction. In this problem, 10 best fitness value samples are selected and 10 other lucky few samples are selected to help in the next generation.

After selecting parents, the genetic searching procedure is progressed by crossover operation. A crossover point can be chosen within the genes for mating each pair of parents. Crossover operators can be a single-point crossover, two-point crossover, or cyclic crossover. Single point fragmentation of two parents is used in single-point crossover and genes of two parents are exchanged among themselves until the crossover point is reached by creating offspring.

For this problem, among 30 new individuals of the next-generation; the first 10 will be the best fitness samples, and the remaining 20 individuals will be generated using 10 best samples and 10 lucky few samples by mating where each mating operation will generate two new children. In the mating operation, each bit of individuals will be used for crossover operation. After the crossover, again 30 individuals will be in the new population. If the newly created individual is feasible with respect to the constraints, then it is added to the population, or another child is created.

Offspring produced by crossover have to go through the mutation mechanism. Mutation helps the algorithm not to be trapped in local optimum and premature convergence. One or more values of genes in a chromosome are altered from its' initial state through mutation. Here random resetting mutation operator is used where the random variable is added to random columns for changing the genes. For creating some more variations within solutions, mutate operation with a probability of 10% will be applied to each individual. Randomly a gene is selected and mutated randomly as 1 or 0 if the mutation probability becomes true and mutate individuals become feasible with respect to the constraints.

During crossover or mutation, it should be checked whether the new individual already exists in the population or not because the same solution in the same population may cause disruptions. If the individual exists in the population, another one should be created.

There are many ways to terminate the execution. For the example problem described here, a total number of generations is used as the termination criteria. Individuals of each generation are the solution to the problem. The fitness value of each individual will be obtained and the chromosome having the smallest fitness value would be selected as the fittest individual and this will be the final solution. This solution will give the location for the facility considering the domino effect.

CHAPTER 5
NUMERICAL EXAMPLE

A numerical example is presented here to have a light on the proposed model. Bangladesh is a disaster-prone country. Here earthquakes are occurring frequently which are creating a risk for any further greater disaster and may lead to multiple disaster incidents. So, determining emergency resource storage facility location by optimal placement of facilities is a very important decision in humanitarian logistics with a view to helping the suffered people.

Bangladesh and the surrounding are divided into nine grid areas. Grid center coordinates is taken as facility location coordinate. Both facility location and demand area location coordinate are considered as same.

Nine grid areas are chosen and Figure 5.1 is showing the candidate facility locations which are denoted as 1 to 9. The box area in Figure 5.1 is indicating the grid area and here candidate facility location 1 is located at the center of the grid. Google Earth Pro Software is used to obtain these coordinates.

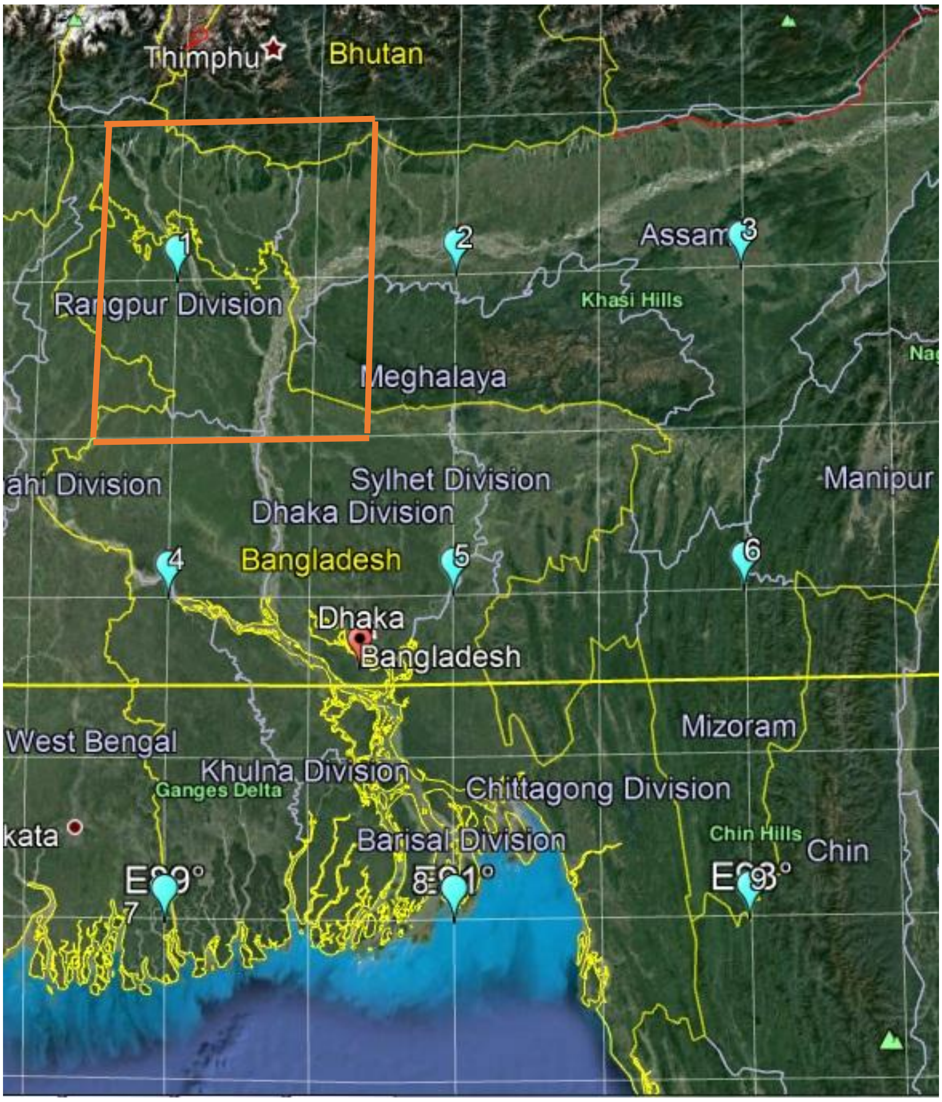


Fig. 5. 1: Indicating candidate facility locations

Table 5.1 is for the coordinates of the candidate facility locations.

Table 5. 1: Coordinates for the candidate facility locations

ID	Latitude	Longitude
1	25.989	89.005
2	25.989	91.003
3	25.989	92.987
4	24.001	89.005
5	24.001	91.003
6	24.001	92.987
7	21.986	89.005
8	21.986	91.003
9	21.986	92.987

Demand areas will be considered the same as the candidate facility locations. The coordinates will also be considered as same as the candidate facility locations.

Coordinates of demand areas are indicated in Table 5.2.

Table 5. 2: Coordinates of demand areas

ID	Latitude	Longitude
1	25.989	89.005
2	25.989	91.003
3	25.989	92.987
4	24.001	89.005
5	24.001	91.003
6	24.001	92.987
7	21.986	89.005
8	21.986	91.003
9	21.986	92.987

For determining transportation cost, distance from facility location to demand area is considered here. So, to obtain these data, QGIS software (version 3.4) is used. Here, at first, the data on coordinates of candidate facility locations and demand areas are converted to CSV (Comma-Separated Values) files and then imported to QGIS software to determine distance matrix where the distance from each facility location to each demand area is calculated through this software. Figure 5.2 shows the determination of distance using QGIS software.

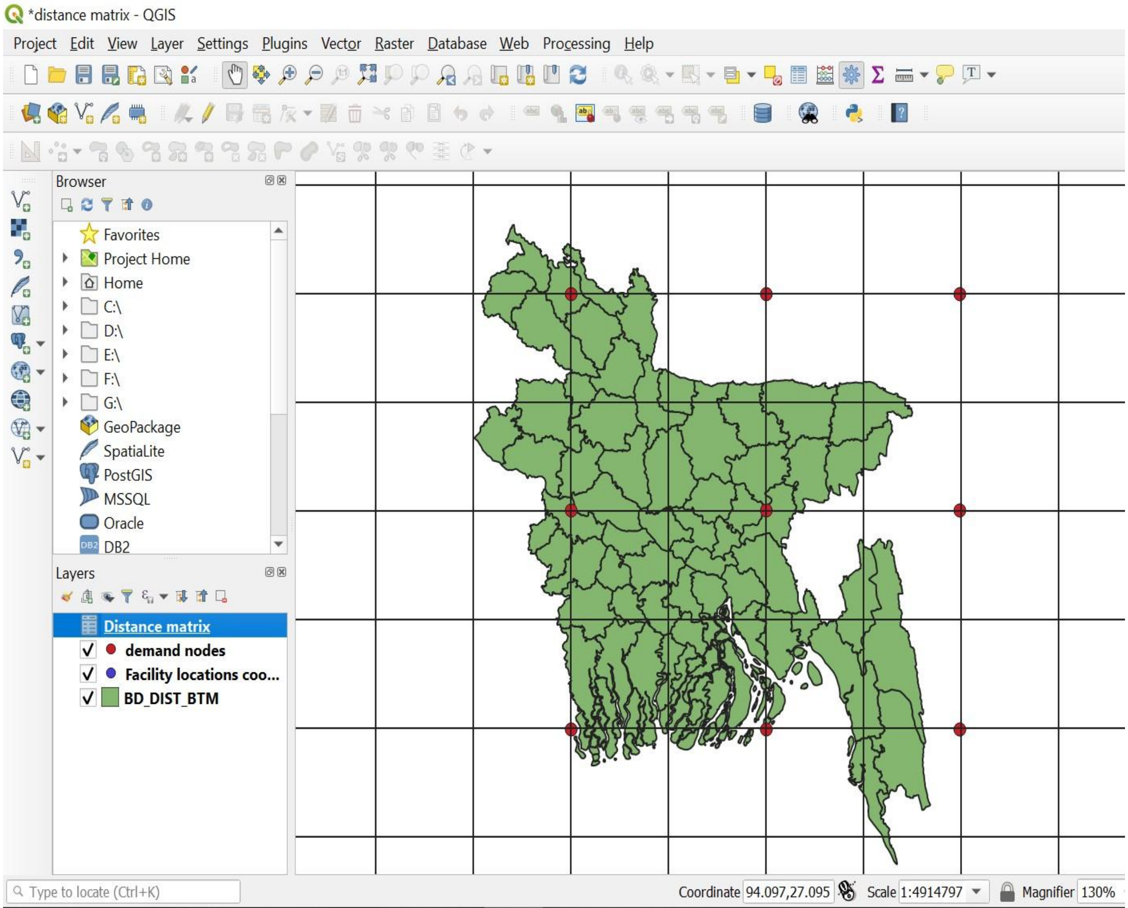


Fig. 5. 2: Determining distance using QGIS software

Table 5.3 indicates the distance between facility location and demand location calculated in km.

Table 5. 3: Distances between facility location and demand areas (in km)

Facility 1	Demand Area	Distance	Facility 2	Demand Area	Distance	Facility 3	Demand Area	Distance	Facility 4	Demand Area	Distance	Facility 5	Demand Area	Distance	Facility 6	Demand Area	Distance	Facilityb7	Demand Area	Distance	Facility 8	Demand Area	Distance	Facility 9	Demand Area	Distance
1	1	0	2	1	201	3	1	399	4	1	221	5	1	299	6	1	459	7	1	444	8	1	488	9	1	601
1	2	201	2	2	0	3	2	199	4	2	299	5	2	221	6	2	298	7	2	488	8	2	444	9	2	488
1	3	399	2	3	199	3	3	0	4	3	459	5	3	298	6	3	221	7	3	601	8	3	488	9	3	444

1	1	1	1	1	1
9	8	7	6	5	4
601	488	444	459	299	221
2	2	2	2	2	2
9	8	7	6	5	4
488	444	488	298	221	299
3	3	3	3	3	3
9	8	7	6	5	4
444	488	601	221	298	459
4	4	4	4	4	4
9	8	7	6	5	4
466	303	224	406	204	0
5	5	5	5	5	5
9	8	7	6	5	4
302	224	303	202	0	204
6	6	6	6	6	6
9	8	7	6	5	4
224	302	466	0	202	406
7	7	7	7	7	7
9	8	7	6	5	4
412	207	0	466	303	224
8	8	8	8	8	8
9	8	7	6	5	4
205	0	207	302	224	303
9	9	9	9	9	9
9	8	7	6	5	4
0	205	412	224	302	466

Transportation cost will be assumed as 250 taka per unit relief item to travel per km multiplied with distance and transferred demand amount. Relief items will be assumed as necessary items given within box. As transportation cost is multiplied with distance, where the location is zero for the same facility area and demand area, transportation cost will also be zero. But it is assumed that there is transportation cost for that case to have the real scenario.

Demand is estimated from the population of all sixty-four districts of Bangladesh considering the probability of occurring primary incident and the probability of domino effect. From the 2011 census, the population for each district is collected [38]. These data are attached in Table 5.4.

Table 5. 4: Population of sixty-four districts [38]

Demand Area	Districts	Demand estimated from population	Total demand ($\times 10^5$)
Area 1	Panchagarh, Thakurgaon, Lalmonirhat, Kurigram, Nilphamari, Dinajpur, Rangpur, Joypurhat, Gaibandha	987,644 1,390,042 1,256,099 2,069,273 1,834,231 2,990,128 2,881,086 913,768 2,379,255	167.02
Area 2	Sherpur, Sunamganj	1,358,325 2,467,968	38.26
Area 3	Sylhet	3,434,188	34.34
Area 4	Naogaon, Chapainawabganj, Rajshahi, Natore, Sirajganj, Bogra, Pabna, Jamalpur, Tangail, Kustia, Meherpur, Chuadanga, Rajbari, Jhenaidah, Faridpur, Magura, Narail, Jessore, Gopalganj, Manikganj	2,600,157 1,647,521 2,595,197 1,706,673 3,097,489 3,400,874 2,523,179 2,292,674 3,605,083 1,946,838 655,392 1,129,015 1,049,778 1,771,304 1,912,969 918,419	389.04

		721,668 2,764,547 1,172,415 1,392,867	
Area 5	Netrokona, Mymensingh, Gazipur, Narsingdi, Munshiganj, Kishoreganj, Habiganj, Dhaka, Narayanganj, Brahamanbaria, Cumilla, Shariatpur, Chandpur, Khagrachhari, Feni, Madaripur	2,229,642 5,110,272 3,403,912 2,224,944 1,445,660 2,911,907 2,089,001 12,043,977 2,948,217 2,840,498 5,387,288 1,155,824 2,416,018 613,917 1,437,371 1,165,952	494.24
Area 6	Maulvibazar	1,919,062	19.19
Area 7	Satkhira, Khulna, Pirojpur, Patuakhali, Barguna, Bagerhat	1,985,959 2,318,527 1,113,257 1,535,854 892,781 1,476,090	93.22
Area 8	Barisal, Bhola, Jhalkathi, Laxmipur, Noakhali, Chattogram, Cox’s Bazar	2,324,310 1,776,795 682,669 1,729,188 3,108,083 7,616,352	195.27

		2,289,990	
Area 9	Rangamati, Bandarban	595,979 388,335	9.84

The fixed cost of establishing and operating each candidate facility is assumed to be different for different zones as some zones have strong infrastructure to establish facilities and some zones (suppose hilly zones) are difficult to set up facilities. Table 5.5 shows the data.

Table 5. 5: Fixed cost of each candidate facility

ID	Fixed cost (BDT) ($\times 10^5$)
1	800
2	700
3	600
4	500
5	400
6	500
7	700
8	900
9	800

The multiplication factor for unutilized capacity after transferring demand from each facility is assumed to be 5. This multiplication factor is taken so that the effect of unutilized capacity could not be negligible. Table 5.6 shows the data.

Table 5. 6: Multiplication factor for unutilized capacity at each candidate facility

ID	Multiplication factor for unutilized capacity
1	5
2	5
3	5
4	5
5	5
6	5

7	5
8	5
9	5

To estimate the probability of primary incident and domino effect, the grid areas (Figure 5.1) are assumed to have different earthquake risk (high, medium, and low) zones. Area 1, 2, 3, 6, 9 are assumed to have high-risk zones, area 4, 5 in medium risk zones, and area 7, 8 in low-risk zones.

Earthquake is considered here as a primary incident that may lead to building collapse and fire.

To determine the escalation probability, probit function (Y) is used which will relate damage for the factors responsible for the domino effect after an earthquake. With the help of equation 3.3 and equation 3.4, which are,

$Y = -5 + 1.5\ln(factors)$

and

$$\ln(factors) = \ln\begin{pmatrix} number\ of\ building\ per\ square\ kilometer\ and \\ a\ constant \\ indicating\ absence\ or\ presence\ of \\ gas\ line\ or\ industry\ or\ hilly\ or\ coastal\ area \end{pmatrix},$$

probit function is determined and from that using equation 3.2, which is, $P_E = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{Y-5} e^{\frac{-x^2}{2}}dx$, escalation probability is obtained.

To obtain probit function (Y), the number of buildings per square kilometer and a constant is considered. The constant will denote the absence or presence of a gas line or industry or a hilly or coastal area, because, presence of any of these will increase the domino effect. In Bangladesh, many areas do not have gas lines. There are some zones where gas lines are absent and some zones have gas lines. It is assumed here that different zones have different levels of gas lines. A constant K is assumed here as a factor for different levels of gas lines or industrial zones or hilly or coastal area and Z is a variable value indicating different levels of gas lines. Here four levels of gas lines have been taken for nine zones on the map. Level 0 is considered if there are no gas lines, not industrial zone, not hilly, and not coastal area. Level 1 is considered if any of these is present; like whether it is hilly area or slightly coastal area or there is only just presence of gas lines. Level 2 is for slightly hilly area and presence of gas lines, or some industries and presence of gas lines, or fully coastal area. Finally, level 3 is for high number of industries and densely designed gas lines. If the zone is assumed in level 0, then Z value of it will be 0, and this Z value is assumed to be 5 for level 1, 6 for level 2, and 7 for level 3; and constant K has a value to be assumed as 100. The final constant used here is the multiplication of Z and K. If the number of buildings per square km is N, and the constant used for each area for the absence or presence of gas lines or industry or hilly or coastal area is (Z×K), then equation 3.3 becomes,

$$Y = -5 + 1.5\ln(N + (Z \times K)) \qquad \text{………… (5.1)}$$

Table 5.7 and Table 5.8 summarize this information.

Table 5. 7: Assigning level and constant for each area (as per assumption)

Demand area	Level assigned to each area	Clarification for assigning levels	Constant used for each area for absence or presence of gas lines or industry or hilly or coastal area (Z×K)
Area 1	Level 0	No gas lines, not industrial zone, not hilly, not coastal area	0
Area 2	Level 1	Presence of gas lines	5 × 100 = 500
Area 3	Level 2	Slightly hilly area, presence of gas lines	6 × 100 = 600
Area 4	Level 2	Some industries, presence of gas lines	6 × 100 = 600
Area 5	Level 3	High number of industries, densely designed gas lines	7 × 100 = 700
Area 6	Level 2	Slightly hilly area, presence of gas lines	6 × 100 = 600
Area 7	Level 1	Slightly coastal area	5 × 100 = 500
Area 8	Level 2	Fully coastal area	6 × 100 = 600
Area 9	Level 1	Hilly area	5 ×100 = 500

Table 5. 8: Probability of primary event (earthquake) and the probability of domino effect

Area	Probability of primary event **(P_p)** (assumption)	Escalation probability				Probability of domino effect **($P_p \times P_E$)**
		Number of buildings per square km (assumption) (N)	Constant used for each area for absence or presence of gas lines or industry or hilly or coastal area (Z×K)	Probit function (Y) $[Y = -5 + 1.5\ln(N + (Z \times K))]$	Escalation probability $\left[\boldsymbol{P_E = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{Y-5} e^{\frac{-x^2}{2}} dx}\right]$	
Area 1 (high-risk zone)	**0.7**	100	0	$Y = -5 + 1.5(\ln(100 + 0)) = 1.91$	**0.001**	**0.0007**
Area 2 (high-risk zone)	**0.7**	50	5 ×100 = 500	$Y = -5 + 1.5(\ln(50 + 500)) = 4.46$	**0.29**	**0.203**
Area 3 (high-risk zone)	**0.7**	70	6 × 100 = 600	$Y = -5 + 1.5(\ln(70 + 600)) = 4.76$	**0.41**	**0.287**
Area 4 (medium risk zone)	**0.6**	500	6 × 100 = 600	$Y = -5 + 1.5(\ln(500 + 600)) = 5.50$	**0.69**	**0.414**
Area 5 (mediu	**0.6**	950	7 × 100 = 700	$Y = -5 + 1.5(\ln(950 +$	**0.87**	**0.522**

m risk zone)				700)) = 6.11		
Area 6 (high-risk zone)	**0.7**	60	$6 \times 100 = 600$	$Y = -5 + 1.5(\ln(60 + 600)) = 4.74$	**0.40**	**0.28**
Area 7 (low-risk zone)	**0.5**	50	$5 \times 100 = 500$	$Y = -5 + 1.5(\ln(50 + 500)) = 4.46$	**0.29**	**0.145**
Area 8 (low-risk zone)	**0.5**	60	$6 \times 100 = 600$	$Y = -5 + 1.5(\ln(60 + 600)) = 4.74$	**0.40**	**0.2**
Area 9 (high-risk zone)	**0.7**	70	$5 \times 100 = 500$	$Y = -5 + 1.5(\ln(70 + 500)) = 4.52$	**0.32**	**0.224**

Capacity has been taken by some random number generation. These are generated in Excel files and then converted to CSV files. Table 5.9 describes this.

Table 5. 9: Capacities of facilities

Capacity ($\times \mathbf{10^5}$)	A random number between 400, 700
	A random number between 500, 800
	A random number between 600, 900
	A random number between 700, 1000

CHAPTER 6

RESULTS AND DISCUSSIONS

This is a theoretical work. The decision variables of the proposed model will give optimal placement of facilities and the number of resources that may be transferred to minimize cost and unutilized capacity. The numerical problem mentioned above is solved using Python software with Gurobi Solver and then genetic algorithm, and the integrated development environment (IDE) is PyCharm. The problem is solved using processor Intel(R) Core(TM) i7-7700 CPU @ 3.60GHz, RAM 8.00 GB, and 64-bit Operating System.

6.1 Gurobi Solver

Gurobi solver is a mathematical programming solver. A prepared model of the problem is given by the user and this solver applies mixed-integer linear programming techniques for finding the optimal solution. To enter algebraic formulations to the solver, a file format called .lp file has to create with the mathematical formulas of the problem.

Gurobi solver can easily interpret the .lp file format. This starts with the line such as ‘maximize’ or ‘minimize’. The solver will calculate the objective function which is written in the second line. The third line consists of ‘subject to’ with the constraint equations. Headers like ‘bounds’, ‘integers’, and ‘binaries’ are used afterwards to indicate the type of variables.

```
Maximize
  x + y + z
Subject To
  c0: x + y = 1
  c1: x + 5 y + 2 z <= 10
  qc0: x + y + [ x ^ 2 - 2 x * y + 3 y ^ 2 ] <= 5
Bounds
  0 <= x <= 5
  z >= 2
Generals
  x y z
End
```

Fig. 6. 1: LP format example [39]

In this problem, the first line is ‘minimize’ as this problem is a minimization problem. The second-line is an objective function which includes the fixed cost of opening facilities, transportation cost from facility to demand areas, and the cost from unutilized capacity in the facility. Constraints of the problem involving customer demand and facility capacities. One of the constraints holds the assumption that there will be no establishment of the facility where there is the maximum probability of domino effect; as domino effect can also damage the facility of that location. For this problem, this is location 5. So, this location will be omitted while taking decisions regarding opening facilities. This is given in ‘bounds’. ‘Integers’ are decision variables regarding the amount of transferred demand from facility to demand area. ‘Binary’ is the decision variable that represents whether the facility will be open or not.

6.2 Genetic Algorithm

The termination criteria of the genetic algorithm is the number of generations. Here, the population size is 30, the number of generations is 50, and the mutation probability is 10%. The number of children will be two after each mating operation of crossover. Each generation will have a population size of 30. The number of generations is 50 because the code has been run also for 50,000 generations which do not show any improvement in optimization. So, 50 generations is considered okay for this problem.

6.3 Results and Discussion

For the convenience of calculation, all the units are converted to the units of 10^5.

As two cases have been considered here, results of two cases have been represented separately. Case I is without constraint on number of facilities and Case II is considering constraint on number of facilities. Weightage have been given for two parts of objective function. Three weightages have been considered.

Table 6. 1: Weightage for two parts of objective function

	Cost part	Unutilized Capacity Part
Weightage	0.3	0.7
	0.5	0.5
	0.7	0.3

6.3.1 Case I

As capacities have been taken from random number generation, so how fitness or objective function is changed along with capacity can be observed. It has been noticed that, for this problem, when the weightages are 0.3 (cost part) and 0.7 (unutilized capacity part) and 0.7 (cost part) and 0.3 (unutilized capacity part); the fitness of the objective function is highest for capacity range between 700 to 1000. The fitness are more optimized for capacity range 600 to 900 and 400 to 700 respectively for the weightages. For weightage 0.5 (cost part) and 0.5 (unutilized capacity part) the highest fitness is for capacity range 400 to 700 and lowest fitness is for capacity range 600 to 900. In most of the cases genetic algorithm shows good performance than Gurobi solver. Figure 6.2 shows changing of fitness while changing capacity range for weightage 0.3 (cost part) and 0.7 (unutilized capacity part).

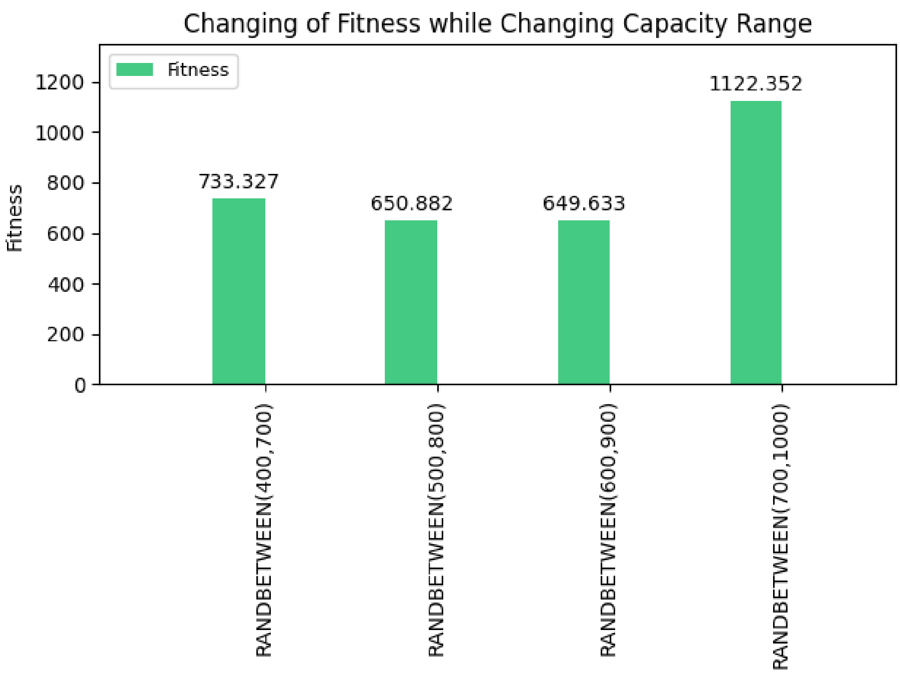


Fig. 6. 2: Changing of fitness while changing capacity range for weightage 0.3 (cost part) and 0.7 (unutilized capacity part)

Figure 6.3 shows changing of fitness while changing capacity range for weightage 0.5 (cost part) and 0.5 (unutilized capacity part).

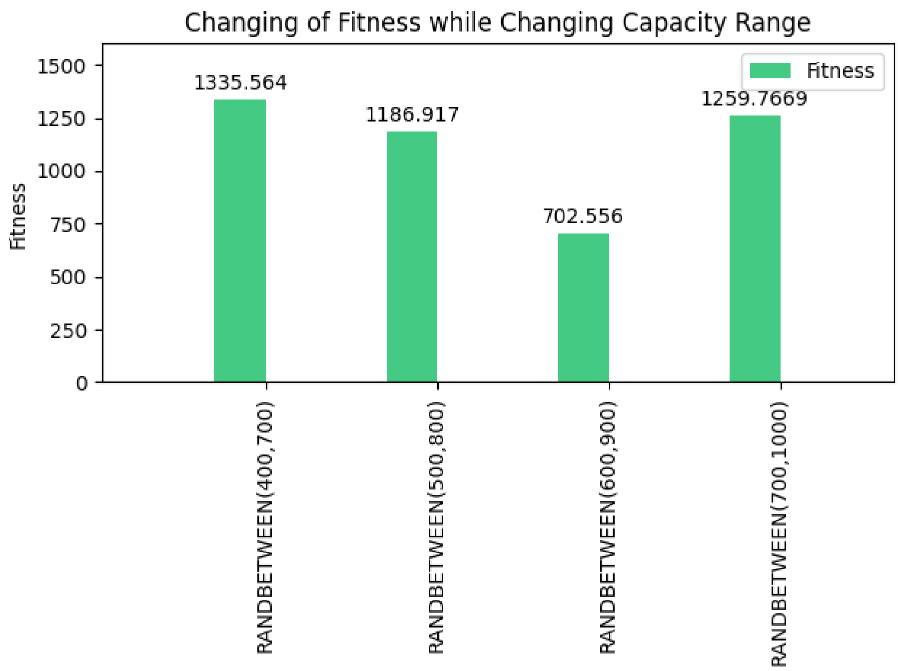


Fig. 6. 3: Changing of fitness while changing capacity range for weightage 0.5 (cost part) and 0.5 (unutilized capacity part)

Figure 6.4 shows changing of fitness while changing capacity range for weightage 0.7 (cost part) and 0.3 (unutilized capacity part).

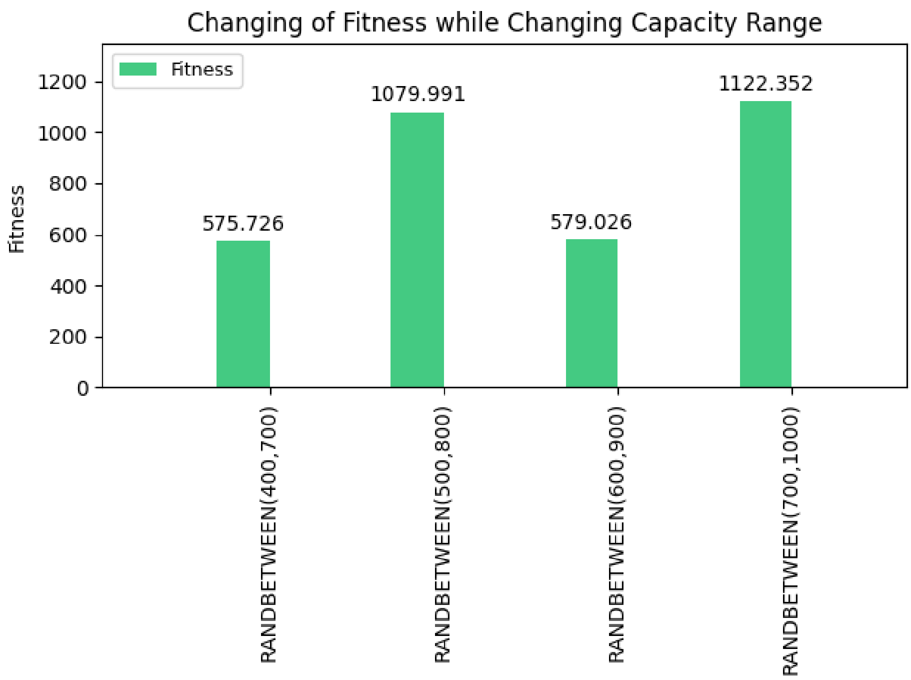
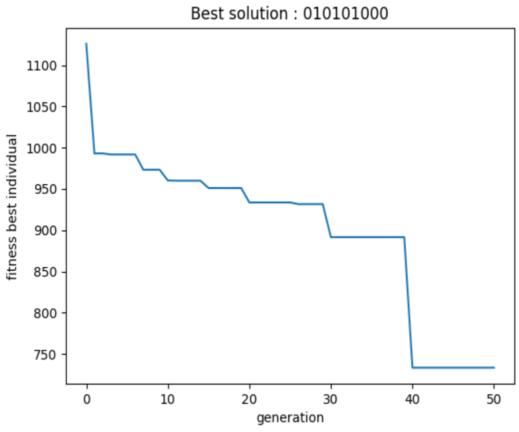
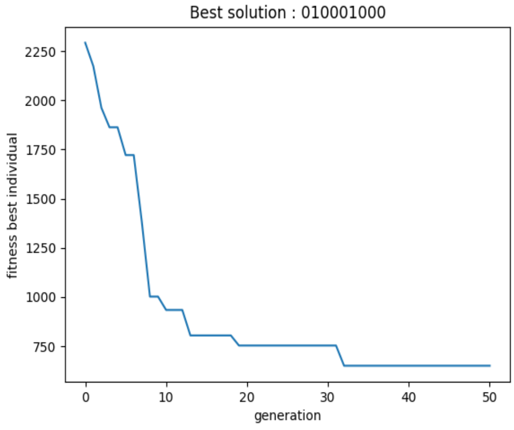


Fig. 6. 4: Changing of fitness while changing capacity range for weightage 0.7 (cost part) and 0.3 (unutilized capacity part).

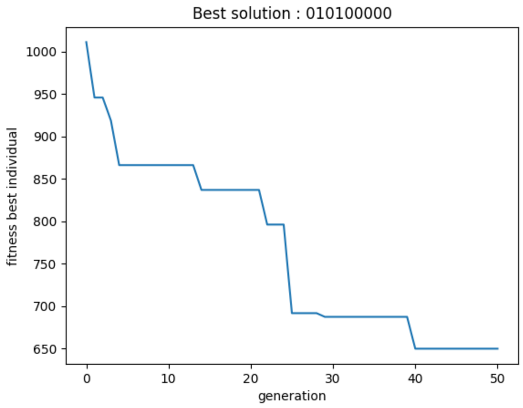
For weightage 0.3 (cost part) and 0.7 (unutilized capacity part), optimum solution (Genetic Algorithm) for different capacity range have been represented in the following figure 6.5. Here best solution 01010100 means facility area 2, 4, 6 are selected here.



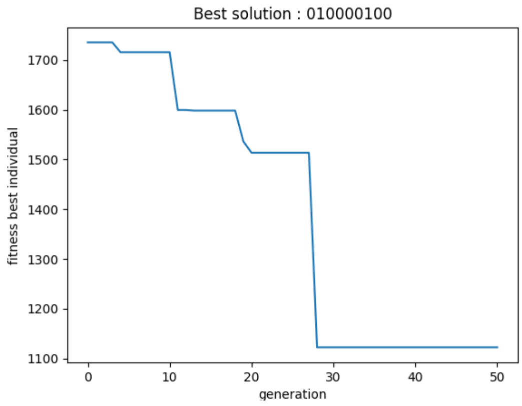
(a)



(b)



(c)



(d)

Fig. 6. 5: Optimum solution for different capacity range (a) 400 to 700 (b) 500 to 800 (c) 600 to 900 (d) 700 to 1000 - weightage 0.3 (cost part) and 0.7 (unutilized capacity part)

It is observed that, when the capacity range is increasing, the number of facilities to establish is decreasing. When the capacity range is 400 to 700, the number of facilities is three where it is two when the capacity range is 700 to 1000.

The following figure 6.6 compares the fitness and time between Genetic Algorithm and Gurobi Solver.

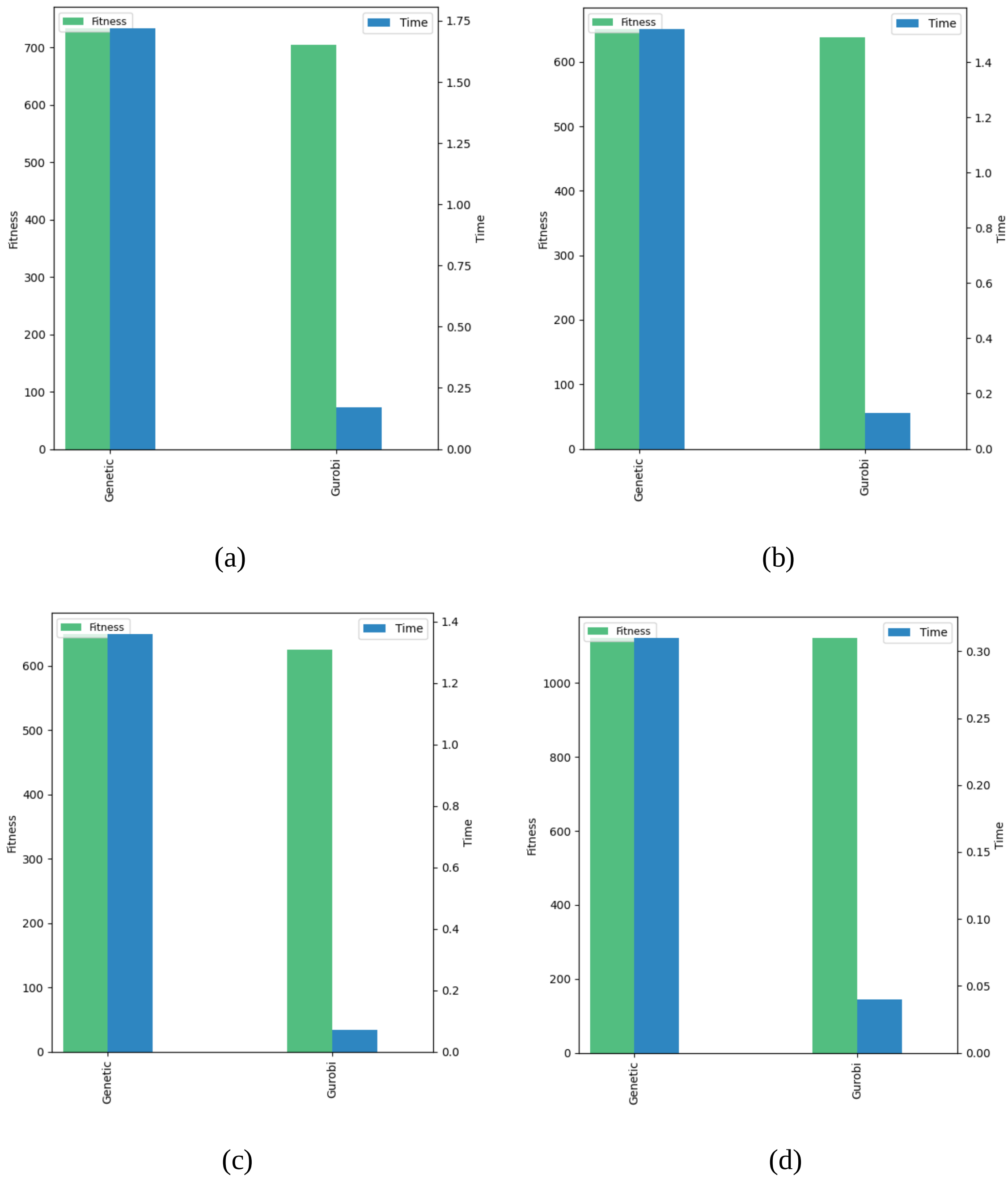


Fig. 6. 6: Comparing the fitness and time between Genetic Algorithm and Gurobi Solver for different capacity range (a) 400 to 700 (b) 500 to 800 (c) 600 to 900 (d) 700 to 1000 - weightage 0.3 (cost part) and 0.7 (unutilized capacity part)

Figure 6.6 indicates that, Gurobi Solver is giving slightly better performance here (both fitness and time) than Genetic Algorithm when weightage is 0.3 (cost part) and 0.7 (unutilized capacity part).

The transferred amount of demand can be obtained for each of these cases. Like, when the capacity range is 400 to 700 for weightage is 0.3 (cost part) and 0.7 (unutilized capacity part), for Genetic Algorithm, the optimum value is 733.32 ($\times 10^5$), the selected optimum facilities are three and the transferred amount from facilities are –

Table 6. 2: Demand transferred ($\times 10^5$) to demand area from facility area (Genetic Algorithm)

Facility Area	Demand Area								
	1	2	3	4	5	6	7	8	9
1	0	0	0	0	0	0	0	0	0
2	118	35	34	0	0	13	61	137	10
3	0	0	0	0	0	0	0	0	0
4	0	0	0	395	147	0	0	0	0
5	0	0	0	0	0	0	0	0	0
6	0	0	0	0	408	6	0	0	0
7	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0

Whereas, for the same case, Gurobi Solver has optimum value 705.00 ($\times 10^5$), the selected optimum facilities are three and the transferred amount from facilities are –

Table 6. 3: Demand transferred ($\times 10^5$) to demand area from facility area (Gurobi Solver)

Facility Area	Demand Area								
	1	2	3	4	5	6	7	8	9
1	0	0	0	0	0	0	0	0	0
2	118	35	34	0	221	0	0	0	0
3	0	0	0	0	0	0	0	0	0
4	0	0	0	395	86	0	61	0	0
5	0	0	0	0	0	0	0	0	0
6	0	0	0	0	248	19	0	137	10
7	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0

For weightage 0.5 (cost part) and 0.5 (unutilized capacity part), optimum solution (Genetic Algorithm) for different capacity range have been represented in the following figure 6.7.

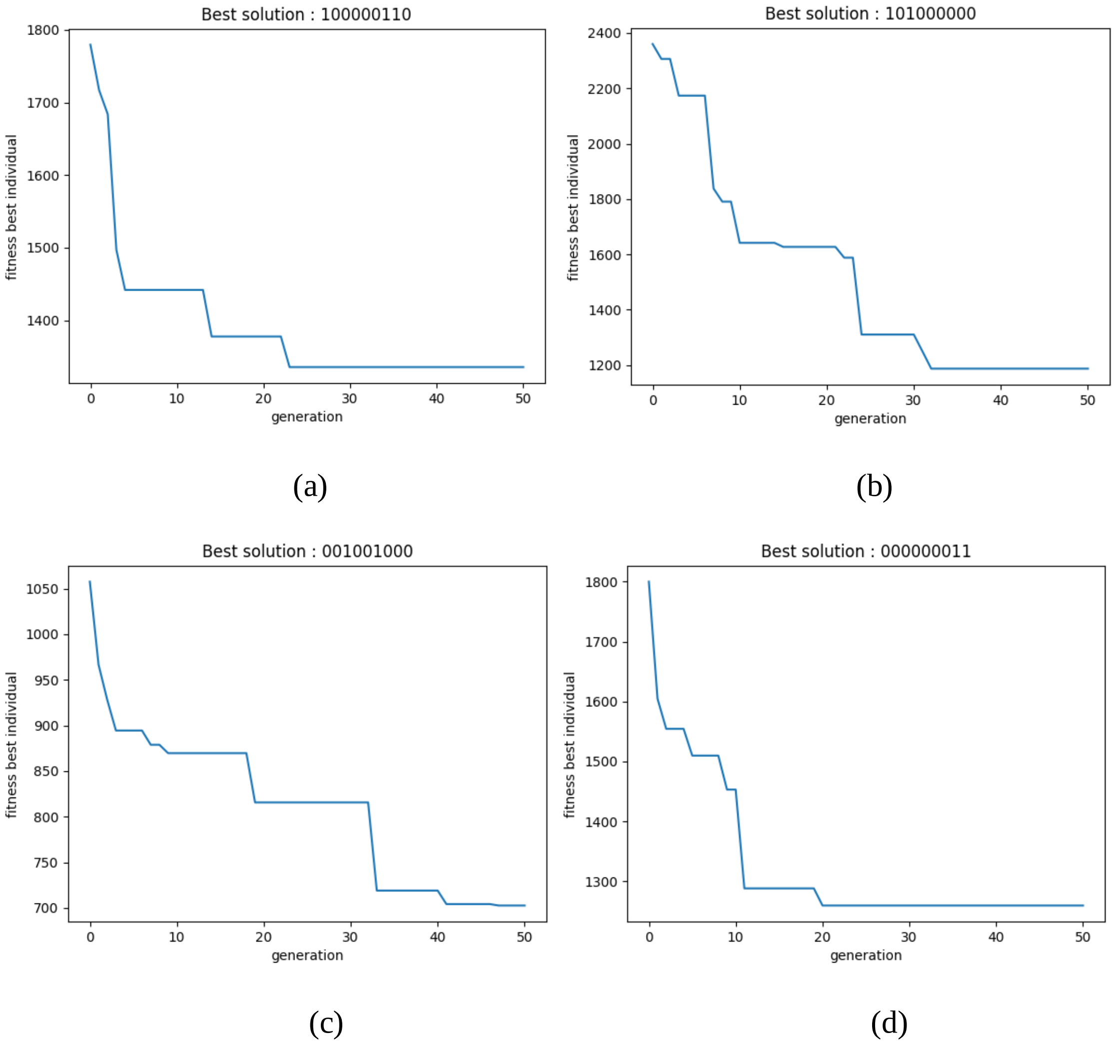


Fig. 6. 7: Optimum solution for different capacity range (a) 400 to 700 (b) 500 to 800 (c) 600 to 900 (d) 700 to 1000 - weightage 0.5 (cost part) and 0.5 (unutilized capacity part)

When the capacity range is increasing, the number of facilities to establish is decreasing like previous example. When the capacity range is 400 to 700, the number of facilities is three where it is two when the capacity range is 700 to 1000.

Figure 6.8 compares the fitness and time between Genetic Algorithm and Gurobi Solver.

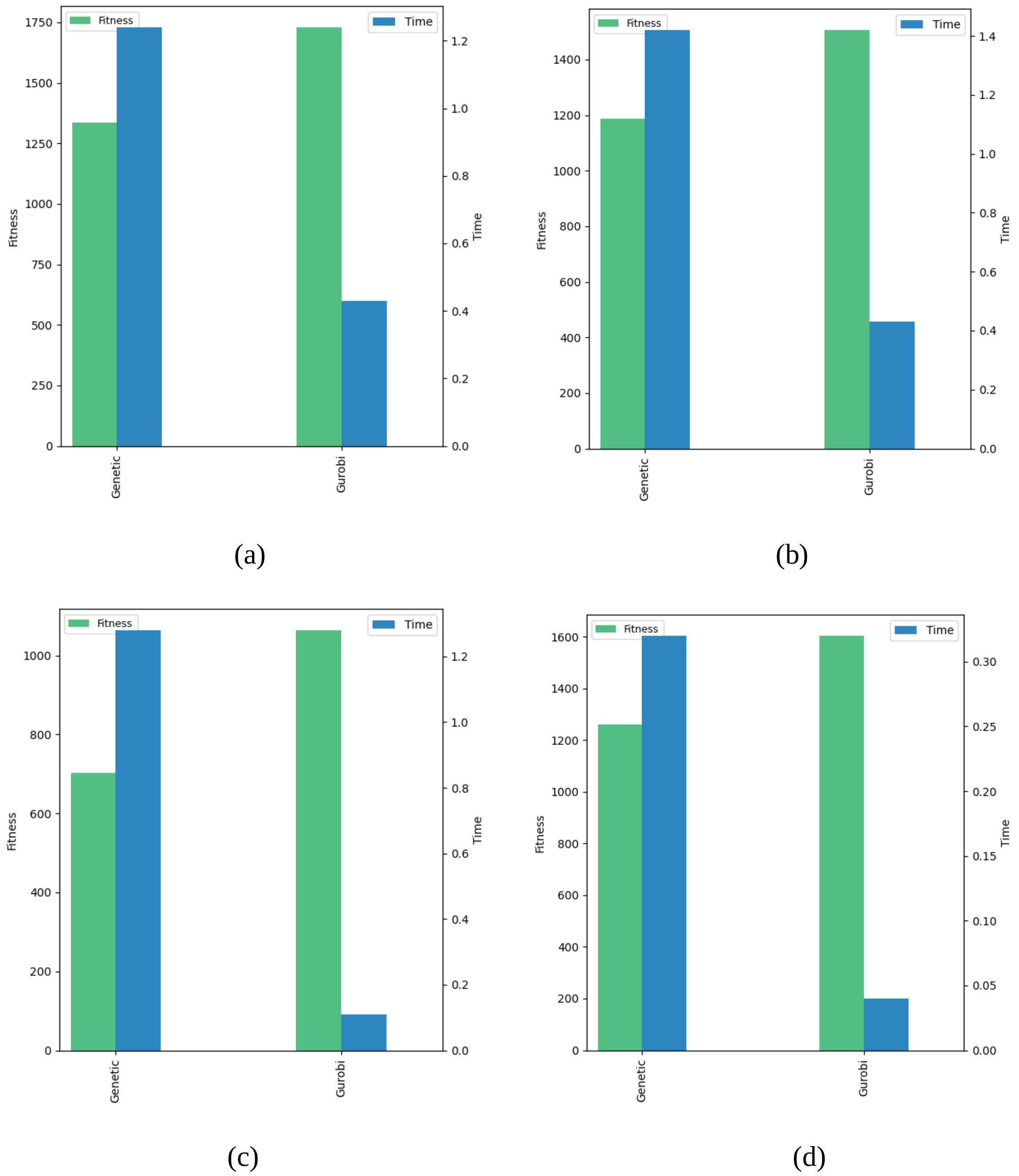
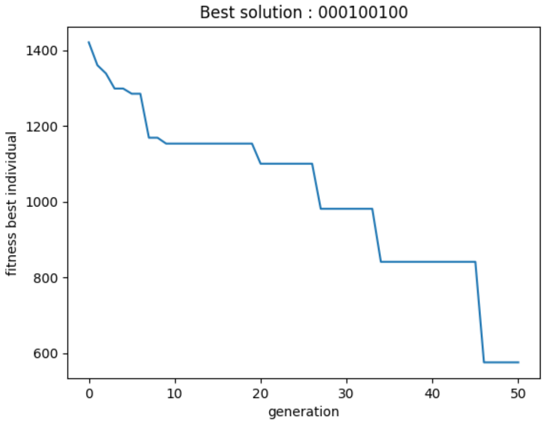


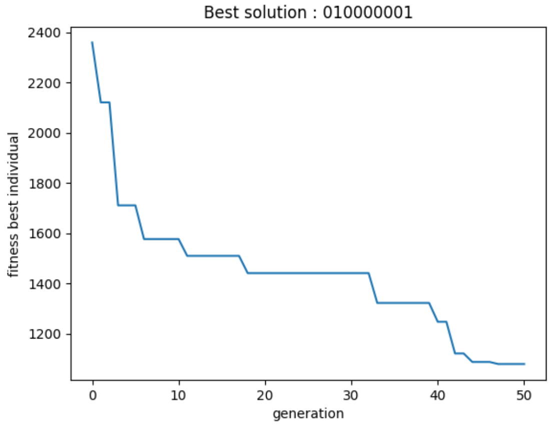
Fig. 6. 8: Comparing the fitness and time between Genetic Algorithm and Gurobi Solver for different capacity range (a) 400 to 700 (b) 500 to 800 (c) 600 to 900 (d) 700 to 1000 - weightage 0.5 (cost part) and 0.5 (unutilized capacity part)

From the figure 6.8, it can be observed that, though Genetic Algorithm takes more time than Gurobi Solver, it gives better performance with respect of fitness than Gurobi Solver.

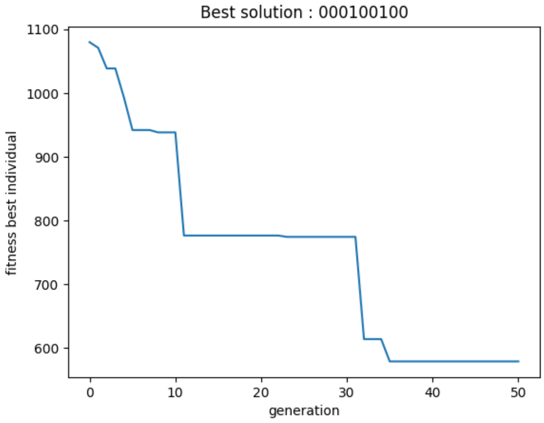
For weightage 0.7 (cost part) and 0.3 (unutilized capacity part), optimum solution (Genetic Algorithm) for different capacity range have been represented in the following figure 6.9.



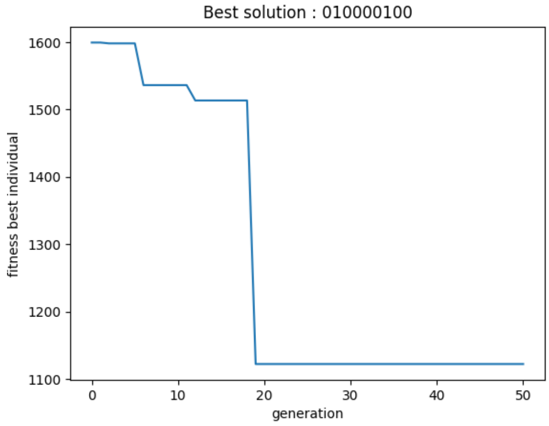
(a)



(b)



(c)



(d)

Fig. 6. 9: Optimum solution for different capacity range (a) 400 to 700 (b) 500 to 800 (c) 600 to 900 (d) 700 to 1000 - weightage 0.7 (cost part) and 0.3 (unutilized capacity part)

Figure 6.10 compares the fitness and time between Genetic Algorithm and Gurobi Solver.

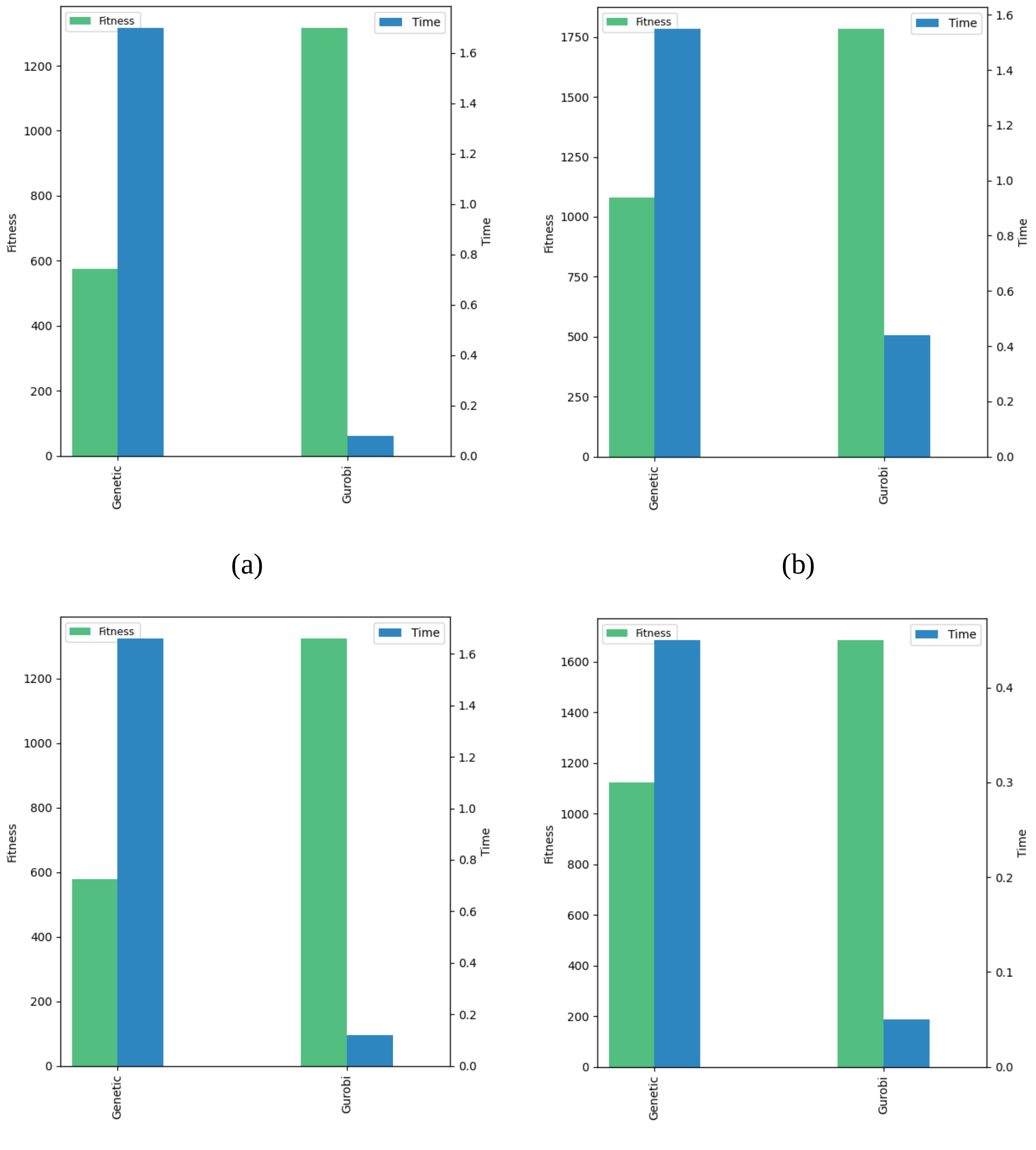


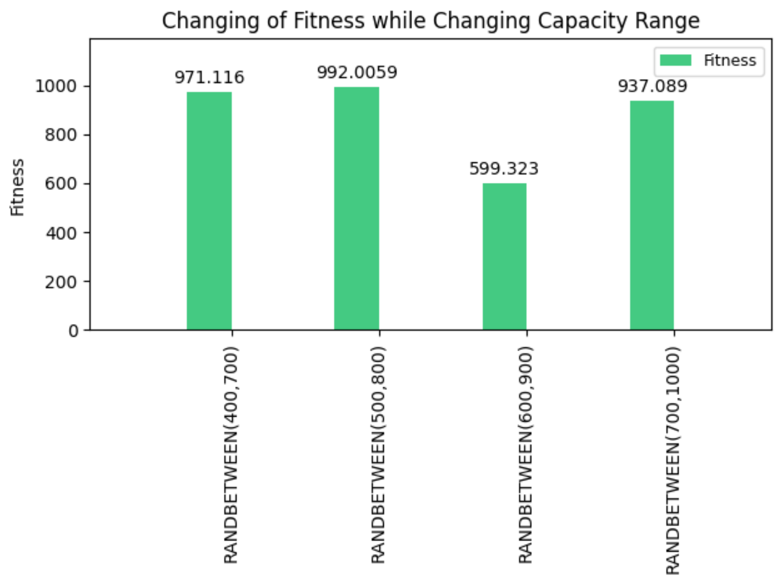
Fig. 6. 10: Comparing the fitness and time between Genetic Algorithm and Gurobi Solver for different capacity range (a) 400 to 700 (b) 500 to 800 (c) 600 to 900 (d) 700 to 1000 - weightage 0.7 (cost part) and 0.3 (unutilized capacity part)

Figure 6.10 indicates that Genetic Algorithm gives better performance than Gurobi Solver.

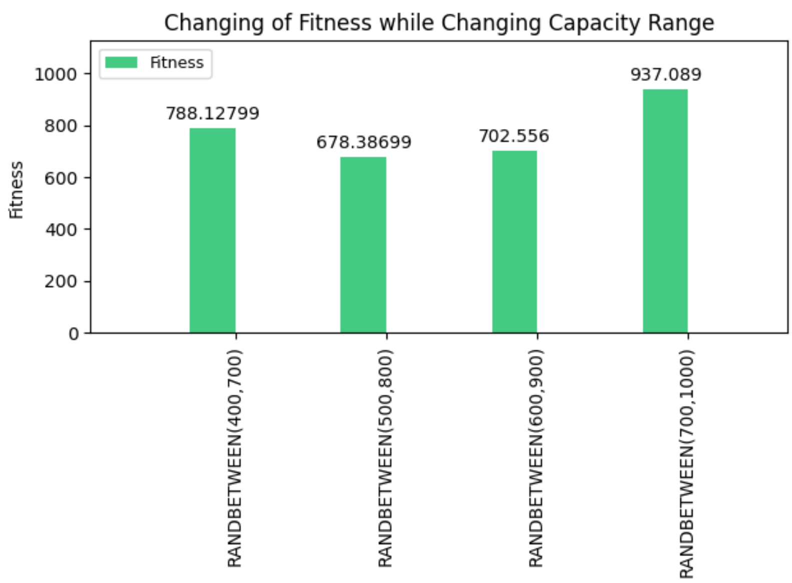
6.3.2 Case II

Case II is considering constraint on number of facilities which is three here. That means, maximum three facilities can be established. This can happen when there is budget limitation for any situation.

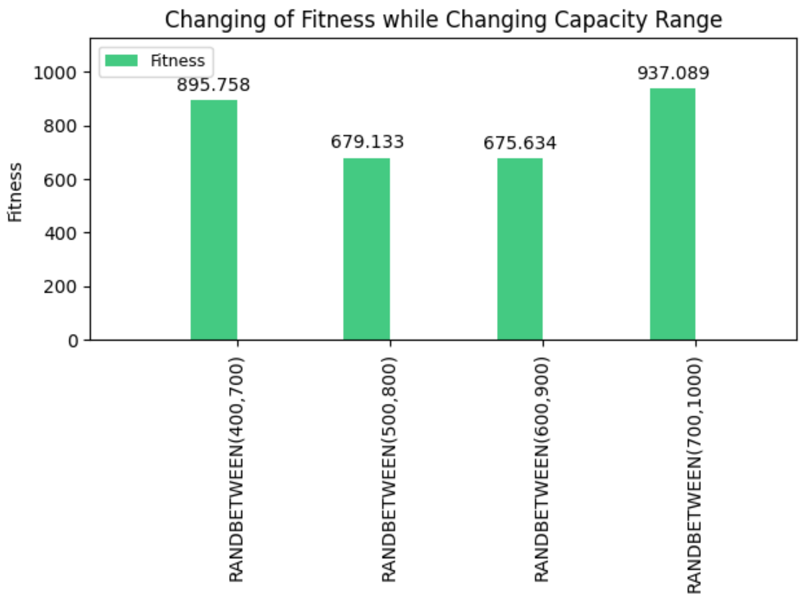
Figure 6.11 shows the changing of fitness for different capacity range (with constraint).



(a)



(b)

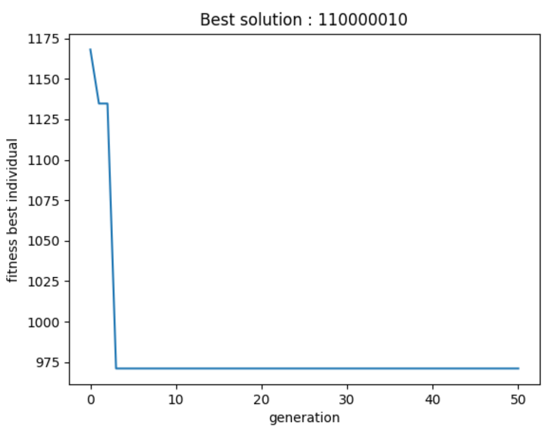


(c)

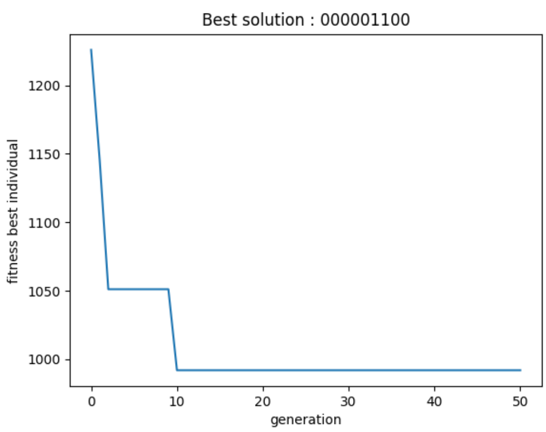
Fig. 6. 11: Changing of fitness (with constraint) while changing capacity range for weightage (a) 0.3 (cost part) and 0.7 (unutilized capacity part), (b) 0.5 (cost part) and 0.5 (unutilized capacity part) (c) 0.7 (cost part) and 0.3 (unutilized capacity part)

This figure shows that, weightage 0.3 (cost part) and 0.7 (unutilized capacity part), and weightage 0.7 (cost part) and 0.3 (unutilized capacity part) - have most optimized fitness for capacity range 600 to 900. And when the weightage is 0.5 (cost part) and 0.5 (unutilized capacity part), the most optimized fitness is for capacity range 500 to 800.

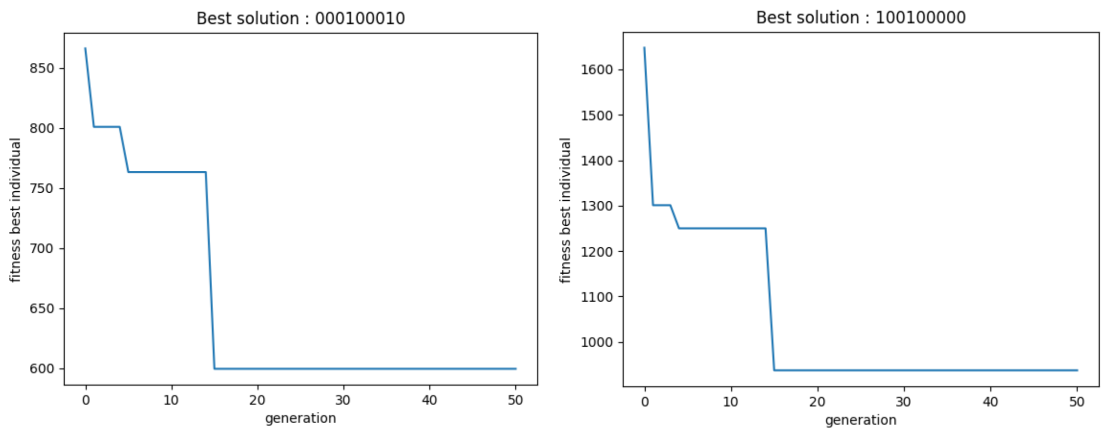
For weightage 0.3 (cost part) and 0.7 (unutilized capacity part), optimum solution (Genetic Algorithm) for different capacity range have been represented in the following figure 6.12.



(a)



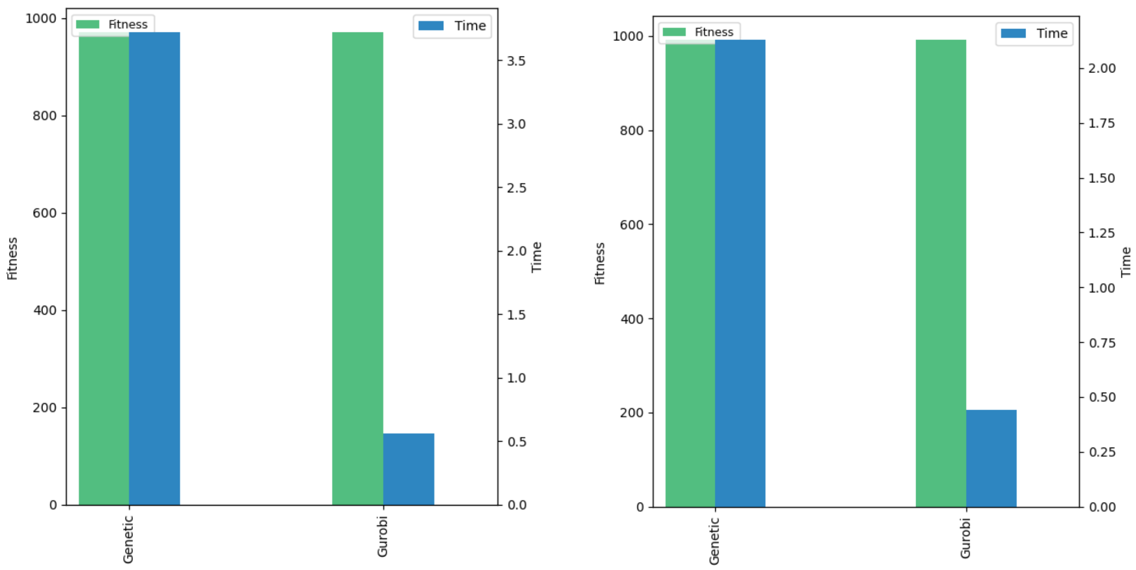
(b)



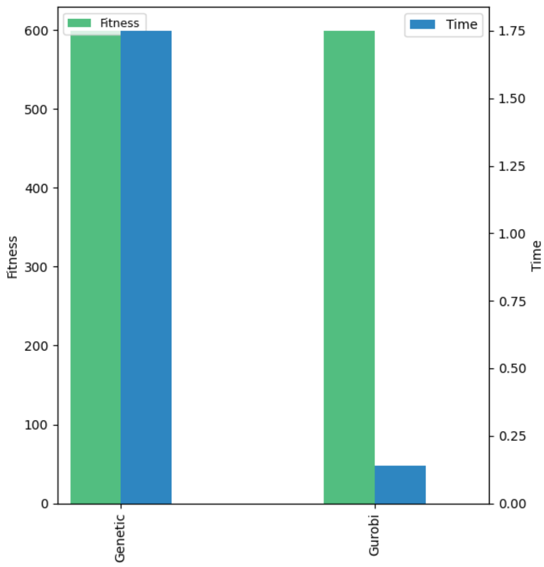
(c) (d)

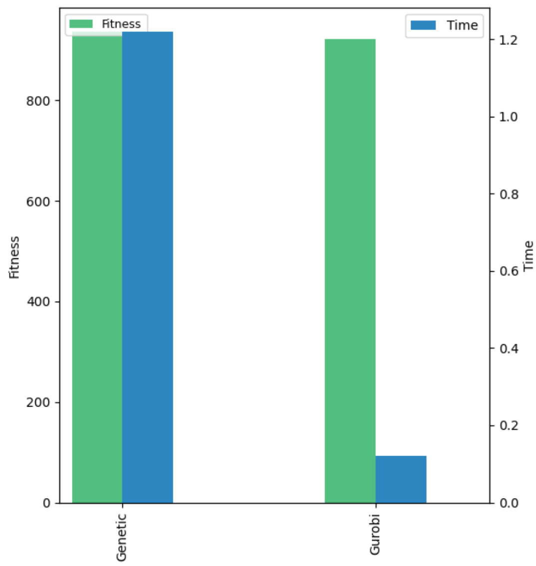
Fig. 6. 12: Optimum solution (with constraint) for different capacity range (a) 400 to 700 (b) 500 to 800 (c) 600 to 900 (d) 700 to 1000 - weightage 0.3 (cost part) and 0.7 (unutilized capacity part)

Figure 6.13 compares the fitness and time between Genetic Algorithm and Gurobi Solver.



(a) (b)



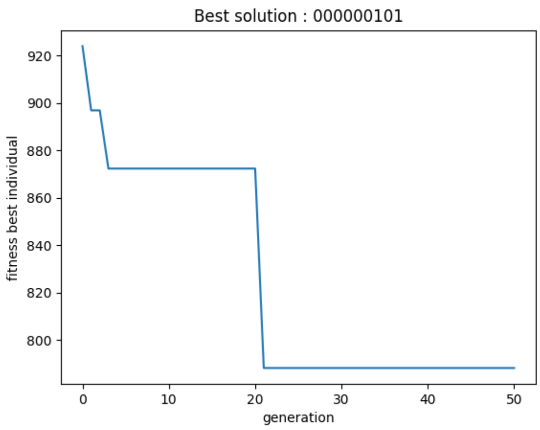


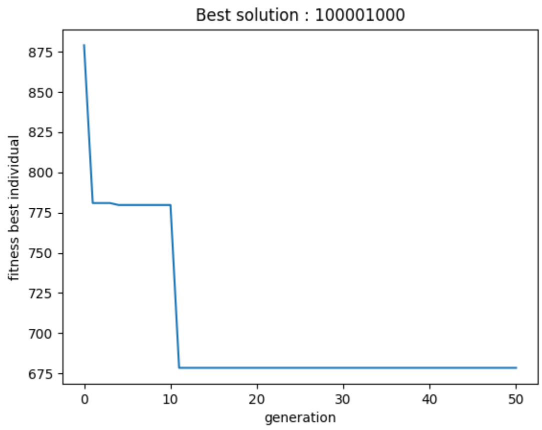
(c) (d)

Fig. 6. 13: Comparing the fitness and time (with constraint) between Genetic Algorithm and Gurobi Solver for different capacity range (a) 400 to 700 (b) 500 to 800 (c) 600 to 900 (d) 700 to 1000 - weightage 0.3 (cost part) and 0.7 (unutilized capacity part)

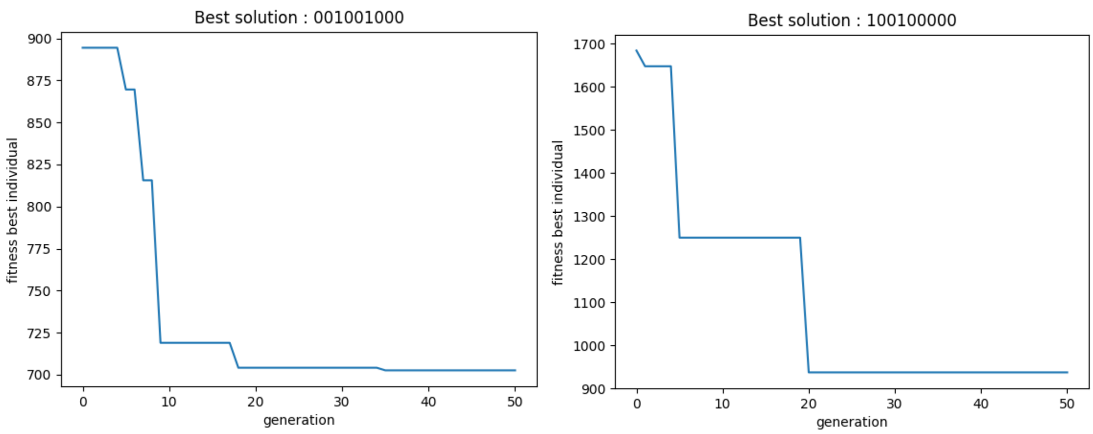
This indicates that, performance of Genetic Algorithm and Gurobi Solver are almost same with respect of fitness.

For weightage 0.5 (cost part) and 0.5 (unutilized capacity part), optimum solution (Genetic Algorithm) for different capacity range have been represented in the following figure 6.14.





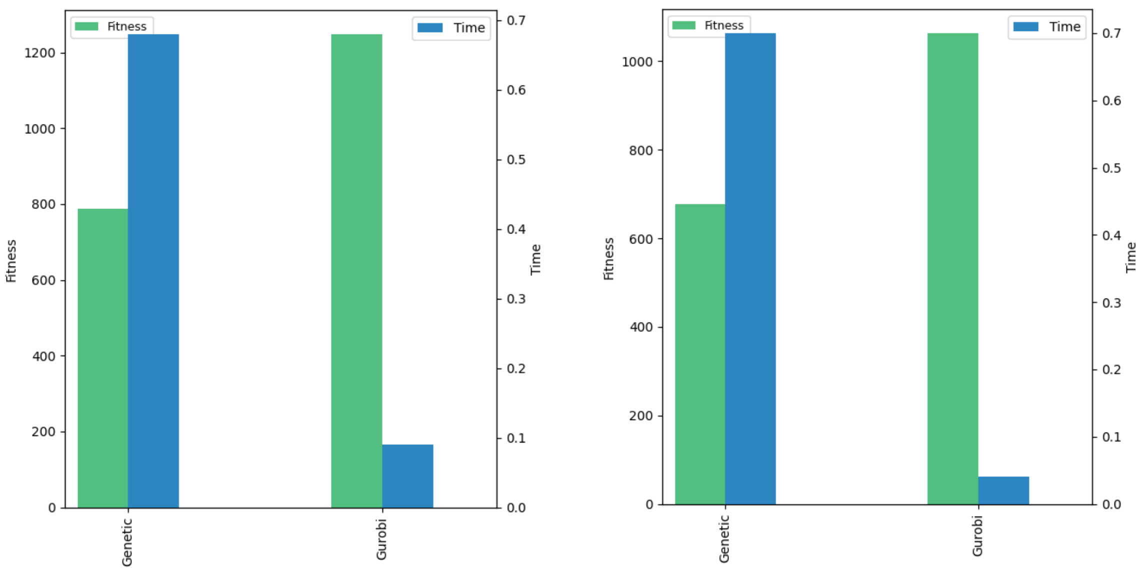
(a) (b)



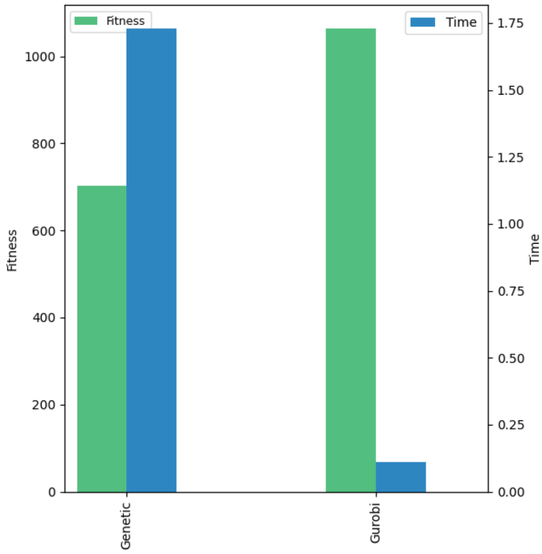
(c) (d)

Fig. 6. 14: Optimum solution (with constraint) for different capacity range (a) 400 to 700 (b) 500 to 800 (c) 600 to 900 (d) 700 to 1000 - weightage 0.5 (cost part) and 0.5 (unutilized capacity part)

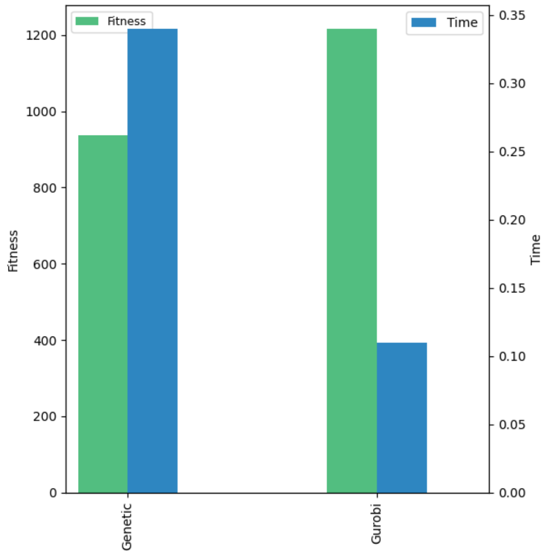
Figure 6.15 compares the fitness and time between Genetic Algorithm and Gurobi Solver.



(a) (b)



(c)

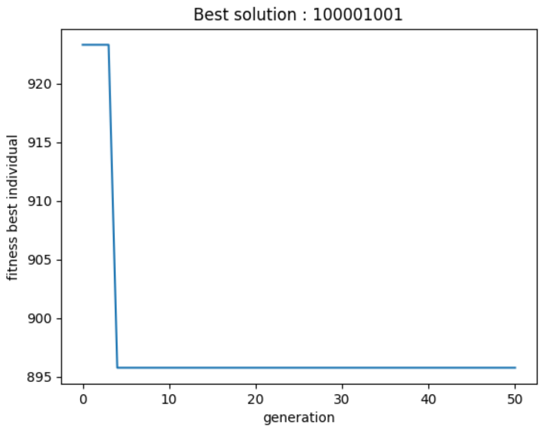


(d)

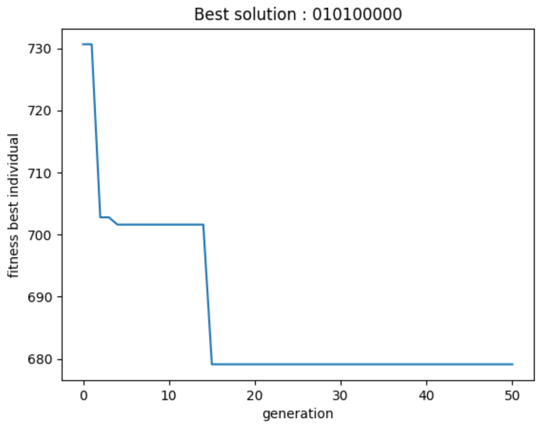
Fig. 6. 15: Comparing the fitness and time (with constraint) between Genetic Algorithm and Gurobi Solver for different capacity range (a) 400 to 700 (b) 500 to 800 (c) 600 to 900 (d) 700 to 1000 - weightage 0.5 (cost part) and 0.5 (unutilized capacity part)

Here, Genetic Algorithm gives better performance with respect to fitness than Gurobi Solver.

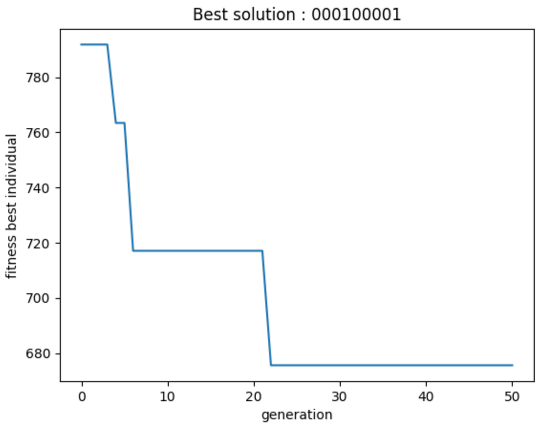
For weightage 0.7 (cost part) and 0.3 (unutilized capacity part), optimum solution (Genetic Algorithm) for different capacity range have been represented in the following figure 6.16.



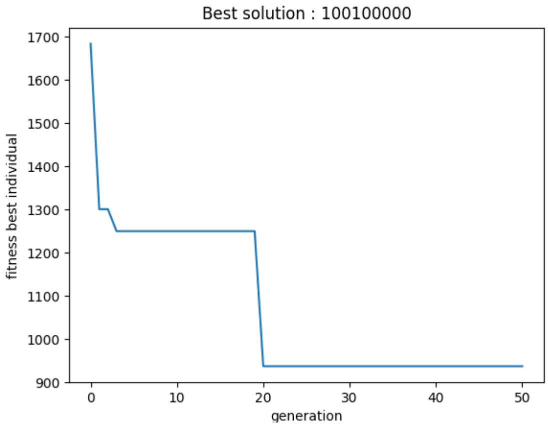
(a)



(b)



(c)

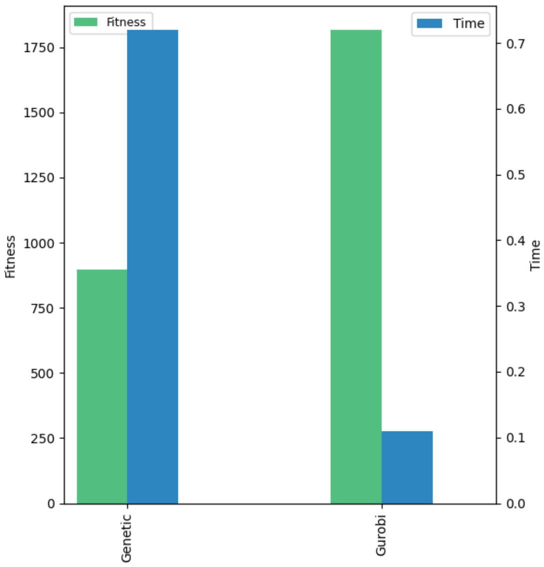


(d)

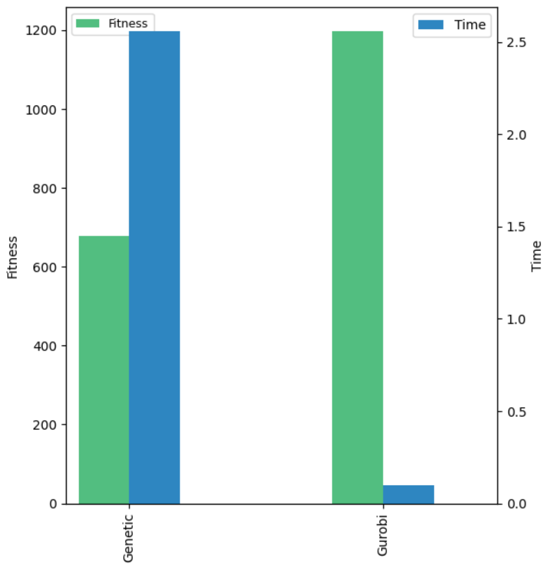
Fig. 6. 16: Optimum solution (with constraint) for different capacity range (a) 400 to 700 (b) 500 to 800 (c) 600 to 900 (d) 700 to 1000 - weightage 0.7 (cost part) and 0.3 (unutilized capacity part)

Like previous examples, it also shows that, the number of facilities is decreasing along with the increase of capacity range.

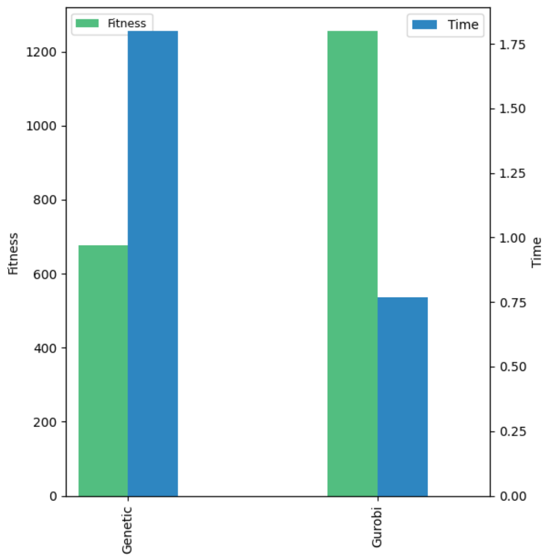
Figure 6.17 compares the fitness and time between Genetic Algorithm and Gurobi Solver.



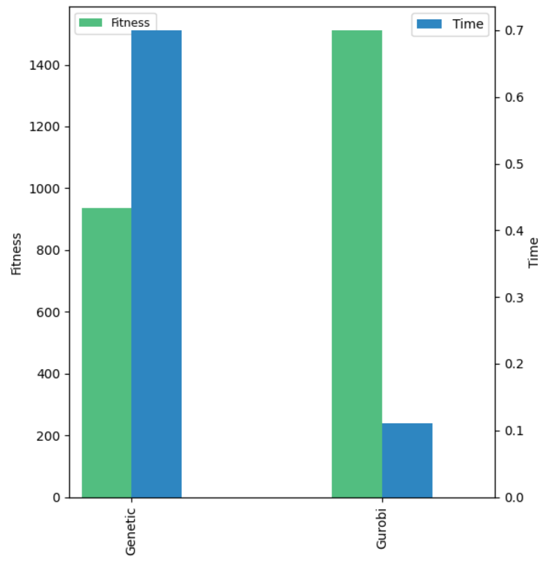
(a)



(b)



(c)



(d)

Fig. 6. 17: Comparing the fitness and time (with constraint) between Genetic Algorithm and Gurobi Solver for different capacity range (a) 400 to 700 (b) 500 to 800 (c) 600 to 900 (d) 700 to 1000 - weightage 0.7 (cost part) and 0.3 (unutilized capacity part)

This also indicates Genetic Algorithm gives better performance than Gurobi Solver.

6.3.3 Pareto optimal front

In multi-objective optimization, there are two or more objective functions. Generally, one feasible solution does not minimize all objective functions simultaneously. So comes the Pareto optimal solutions. These are the solutions that cannot be improved in any of the objective functions without compromising another objective functions. The Pareto optimal solutions are not dominated by other feasible solutions, so these are the non-dominated solutions. Pareto front is called the boundary of the set of Pareto optimal solutions.

Weighted sum method has been used here to obtain Pareto optimal front. For sample example, here Pareto front is obtained for random capacity range 500-800 and considering constraint for facility. The weightage used here is from 0 to 1, incrementing 0.1 at each step. After running the coding in PyCharm, four distinct points are obtained for Gurobi Solver and two distinct points are obtained for Genetic Algorithm.

The following figure 6.18 indicates Pareto optimal front for Gurobi Solver.

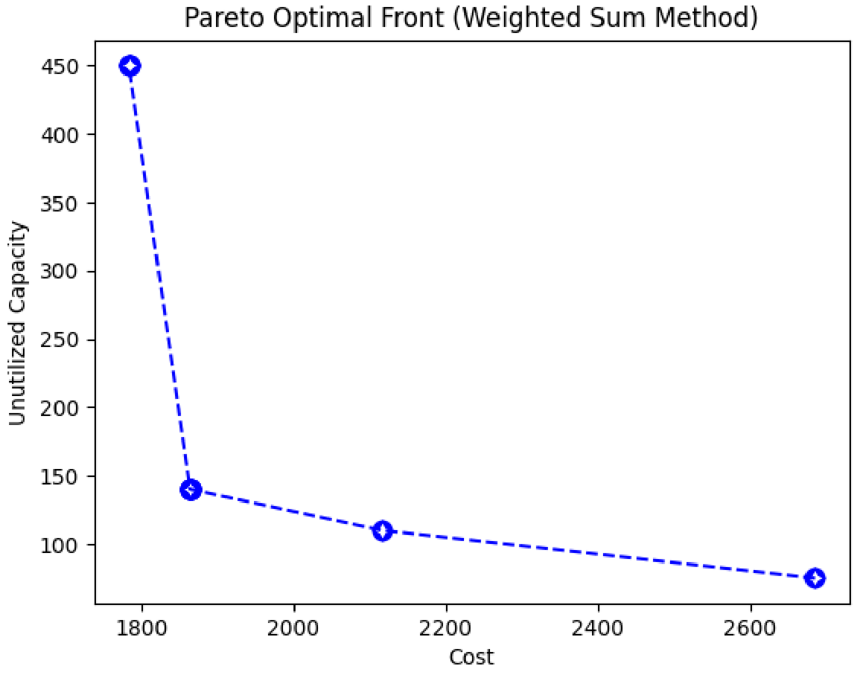


Fig. 6. 18: Pareto Optimal Front (Gurobi Solver)

Here, four points are non-dominated solutions for the problem. These are Pareto optimal solutions. If cost is function one and unutilized capacity is function two, these points are [2685.23, 75.0], [2115.61, 110.0], [1864.41, 140.0], [1783.40, 450.0]. All these points are considered equally good. Decision maker can choose any of these points. If decision maker chooses the optimal point [2115.61, 110.0], then it indicates that, two facilities – facility number 2 and 7 will be chosen. The transferred demand will be like in table 6.4.

Table 6. 4: Demand transferred ($\times 10^5$) to demand area from facility area (Gurobi Solver)

Facility Area	Demand Area								
	1	2	3	4	5	6	7	8	9
1	0	0	0	0	0	0	0	0	0
2	118	35	34	0	518	19	0	0	0
3	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0
7	0	0	0	395	37	0	61	137	10
8	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0

The following figure 6.19 indicates Pareto optimal front for Genetic Algorithm.

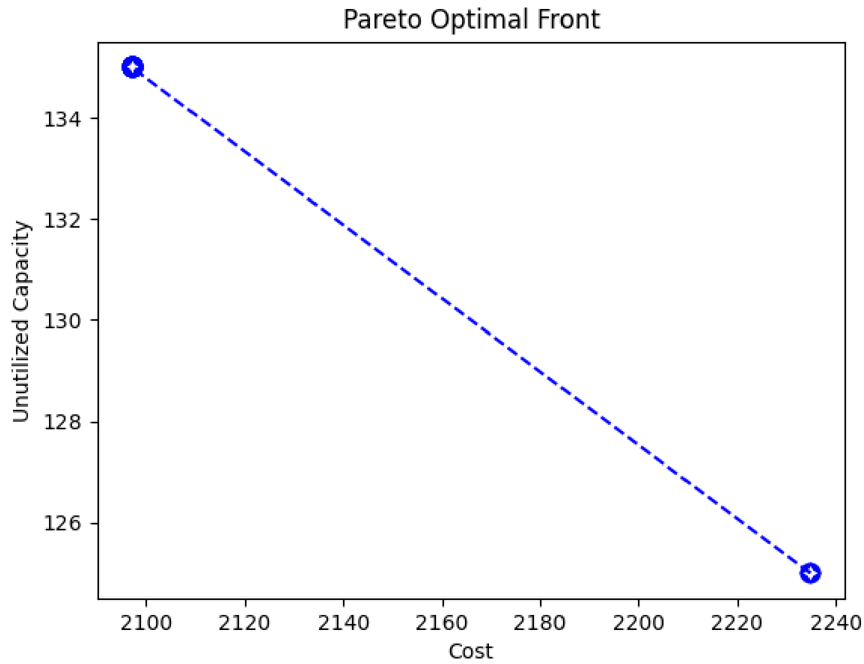


Fig. 6. 19: Pareto Optimal Front (Genetic Algorithm)

Here, two points are Pareto optimal solutions for the problem. If cost is function one and unutilized capacity is function two, these points are [2234.86, 125.0], [2096.99, 135.0]. If decision maker chooses the optimal point [2096.99, 135.0], then it indicates that, two facilities – facility number 2 and 6 will be chosen. The transferred demand will be like in table 6.5.

Table 6. 5: Demand transferred ($\times 10^5$) to demand area from facility area (Genetic Algorithm)

Facility Area	Demand Area								
	1	2	3	4	5	6	7	8	9
1	0	0	0	0	0	0	0	0	0
2	118	35	34	395	0	0	13	137	10
3	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0
6	0	0	0	0	555	19	48	0	0
7	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0

CHAPTER 7

CONCLUSION AND RECOMMENDATION

7.1 Conclusions

The world is facing challenges due to the increased number of natural disasters. It becomes difficult to assist the disaster-affected people if a natural disaster leads to a domino effect. Earthquake is now happening frequently which is an indicator of any big earthquake in near future and there is so much possibility of the domino effect after any big magnitude earthquake. This thesis work has tried to focus on this scenario by identifying the possible facility locations and transferred the amount of demand with the help of the Gurobi solver and genetic algorithm by varying capacity range for the facilities. This may help to select facility locations when the domino effect in the natural disaster is under consideration. By using QGIS software, the distance between candidate facility locations and demand areas has been obtained and PyCharm software helped to solve the optimization problem.

In this proposed model, at first, the probability of the domino effect has been determined by using equations 3.2, 3.3, and 3.4 and the probability of a primary event has been taken as per assumption. The location where the domino effect probability is highest, has been omitted from the selection of establishing the facility as domino effect can affect facilities. After that, from the remaining locations, an optimum number of locations has been selected and the amount of demand which will be transferred from each location has been determined by varying capacity amount in each facility locations.

Two cases have been considered here. One is without constraint and the other is considering constraint for the number of facilities. As this is multi-objective optimization problem, there are two parts of the objective functions. One is cost part and another is unutilized capacity part.

It is observed that, Genetic Algorithm is giving better performance for optimization than Gurobi Solver for most of the situations. As different capacity ranges have been taken randomly, how objective function changes with capacity, has been observed. For most of the situations, when the capacity is increasing and crosses a specific range, the value of the objective function becomes higher. This is because, then the unutilized capacity becomes higher. And it is also obvious that a minimum capacity range is needed to satisfy the demand otherwise the solution will be infeasible. So, decision maker has to be careful for selecting the capacity range. In this model, the optimum facility location for a specific capacity range have been indicated.

Finally, Pareto optimal front has been determined for both Gurobi Solver and Genetic Algorithm. These are the set of Pareto optimal solutions which are equally good optimal solutions. Decision maker can choose any of these points. The corresponding values of decision variables of one Pareto optimal solution has been described here as sample example.

7.2 Recommendation

There may be some possible directions to which this research can be extended.

While determining the domino effect probability, escalation probability had been calculated where probit coefficients were taken after trial and error and to the best of my knowledge, there is no available value of these coefficients due to earthquake. During trial and error, there were some other values for the coefficients, which were not considered. So, further study can be done with these values and it will be highly appreciable to search for the realistic values of these coefficients.

Vehicle routing can be further added to this study to have knowledge of emergency routes.

One can include time to the model which will indicate the amount of time to provide service to the disaster-affected people.

In the present model, a penalty of failure to transfer demand to the affected people is not included, further study can be done with this.

In this model, there are four random capacity range has been under consideration. More study can be done to choose the optimal capacity range by adding more random capacity range to the calculation.

Lastly, one can discover the model considering while there is any shortage of supply from one facility, other facilities can provide this.

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Appendix A - Determine the probit coefficients

Table A. 1: Trial and error to determine the probit coefficients (keeping N, Z, K constant)

Probability of primary event **(P_P)** (assumption)	Escalation probability					Probability of domino effect **($P_P \times P_E$)**
	Number of buildings per square km (assumption) (N)	Constant used for each area for absence or presence of gas lines or industry or hilly or coastal area (Z×K)	Probit function (Y) $[Y = K_1 + K_2 \ln(N + (Z \times K))]$		Escalation probability $[\boldsymbol{P_E} = \frac{\mathbf{1}}{\sqrt{\mathbf{2\pi}}}\int_{-\infty}^{Y-5} \boldsymbol{e}^{\frac{-x^2}{2}} \boldsymbol{dx}]$	
0.7	50	5 ×100 = 500	$K_1 = -1,$ $K_2 = 5$	$Y = -1 + 5(\ln(50 + 500)) = 30.55$	1	0.7
0.7	50	5 ×100 = 500	$K_1 = -2,$ $K_2 = 4$	$Y = -2 + 4(\ln(50 + 500)) = 23.24$	1	0.7
0.7	50	5 ×100 = 500	$K_1 = -3.5,$ $K_2 = 4.5$	$Y = -3.5 + 4.5(\ln(50 + 500)) = 24.89$	1	0.7
0.7	50	5 ×100 = 500	$K_1 = -4,$ $K_2 = 3$	$Y = -4 + 3(\ln(50 + 500)) = 14.93$	0.1	0.07

0.7	50	5 ×100 = 500	$K_1 = -5, K_2 = 2$	$Y = -5 + 2(\ln(50 + 500)) = 7.62$	0.995	0.697
0.7	50	5 ×100 = 500	$K_1 = -5, K_2 = 1.5$	$Y = -5 + 1.5(\ln(50 + 500)) = 4.46$	0.29	0.203
0.7	50	5 ×100 = 500	$K_1 = -5, K_2 = 1$	$Y = -5 + 1(\ln(50 + 500)) = 1.31$	0.00011	7.7×10^{-5}
0.7	50	5 ×100 = 500	$K_1 = -5, K_2 = 0.5$	$Y = -5 + 0.5(\ln(50 + 500)) = -1.85$	3.69×10^{-12}	2.583×10^{-12}
0.7	50	5 ×100 = 500	$K_1 = -6, K_2 = 1$	$Y = -6 + 1(\ln(50 + 500)) = 0.31$	1.37×10^{-6}	9.59×10^{-07}
0.7	50	5 ×100 = 500	$K_1 = -6, K_2 = 0.5$	$Y = -6 + 0.5(\ln(50 + 500)) = -2.85$	2.08×10^{-15}	1.456×10^{-15}
0.7	50	5 ×100 = 500	$K_1 = 5, K_2 = -1.5$	$Y = 5 - 1.5(\ln(50 + 500)) = -4.46$	1.54×10^{-21}	1.078×10^{-21}

Table A. 2: Trial and error to determine the probit coefficients (keeping K_1 , K_2 as constant and by varying N, Z, K)

Probability of primary event **(P_P)** (assumption)	Escalation probability					Probability of domino effect **($P_P \times P_E$)**
	Number of buildings per square km (assumption) (N)	Constant used for each area for absence or presence of gas lines or industry or hilly or coastal area (Z×K)	Probit function (Y) $[Y = K_1 + K_2 \ln(N + (Z \times K))]$		Escalation probability $[P_E = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{Y-5} e^{\frac{-x^2}{2}} dx]$	
0.7	100	5 ×100 = 500	$K_1 = -1$, $K_2 = 5$	$Y = 30.98$	1	0.7
		6 ×100 = 600		$Y = 31.78$	1	0.7
		7 ×100 = 700		$Y = 32.42$	1	0.7
	950	5 ×100 = 500		$Y = 35.40$	1	0.7
		6 ×100 = 600		$Y = 35.73$	1	0.7
		7 ×100 = 700		$Y = 36.04$	1	0.7
0.7	100	5 ×100 = 500	$K_1 = -2$, $K_2 = 4$	$Y = 23.59$	1	0.7
		6 ×100 = 600		$Y = 24.20$	1	0.7
		7 ×100 = 700		$Y = 24.74$	1	0.7
	950	5 ×100 = 500		$Y = 27.12$	1	0.7
		6 ×100 = 600		$Y = 27.38$	1	0.7

		7 ×100 = 700		$Y = 27.63$	1	0.7
0.7	100	5 ×100 = 500	$K_1 = -3.5, K_2 = 4.5$	$Y = 25.29$	1	0.7
		6 ×100 = 600		$Y = 25.98$	1	0.7
		7 ×100 = 700		$Y = 26.58$	1	0.7
	950	5 ×100 = 500		$Y = 29.26$	1	0.7
		6 ×100 = 600		$Y = 29.56$	1	0.7
		7 ×100 = 700		$Y = 29.84$	1	0.7
0.7	100	5 ×100 = 500	$K_1 = -4, K_2 = 3$	$Y = 15.19$	0.1	0.07
		6 ×100 = 600		$Y = 15.65$	0.1	0.07
		7 ×100 = 700		$Y = 16.05$	0.1	0.07
	950	5 ×100 = 500		$Y = 17.84$	0.1	0.07
		6 ×100 = 600		$Y = 18.04$	0.1	0.07
		7 ×100 = 700		$Y = 18.23$	0.1	0.07
0.7	100	5 ×100 = 500	$K_1 = -5, K_2 = 2$	$Y = 7.79$	0.997	0.698
		6 ×100 = 600		$Y = 8.10$	0.999	0.699
		7 ×100 = 700		$Y = 8.37$	0.999	0.699
	950	5 ×100 = 500		$Y = 9.56$	0.999	0.699
		6 ×100 = 600		$Y = 9.70$	0.999	0.699
		7 ×100 = 700		$Y = 9.82$	0.999	0.699
0.7	100	5 ×100 =	K_1	$Y = 4.60$	0.34	0.24

		500	$= -5$,			
		6 ×100 = 600	$K_2 =$ 1.5	$Y = 4.83$	0.43	0.30
		7 ×100 = 700		$Y = 5.03$	0.51	0.36
	950	5 ×100 = 500		$Y = 5.92$	0.82	0.57
		6 ×100 = 600		$Y = 6.02$	0.85	0.595
		7 ×100 = 700		$Y = 6.11$	0.87	0.61
0.7	100	5 ×100 = 500	$K_1 = -5$,	$Y = 1.40$	0.00016	1.12×10^{-4}
		6 ×100 = 600	$K_2 = 1$	$Y = 1.55$	0.00028	1.96×10^{-4}
		7 ×100 = 700		$Y = 1.68$	0.00045	3.15×10^{-4}
	950	5 ×100 = 500		$Y = 2.28$	0.0033	2.31×10^{-3}
		6 ×100 = 600		$Y = 2.34$	0.0039	2.73×10^{-3}
		7 ×100 = 700		$Y = 2.41$	0.0048	3.36×10^{-3}
0.7	100	5 ×100 = 500	$K_1 = -5$,	$Y = -1.80$	5.23×10^{-12}	3.66×10^{-12}
		6 ×100 = 600	$K_2 =$ 0.5	$Y = -1.72$	9.09×10^{-12}	6.36×10^{-12}
		7 ×100 = 700		$Y = -1.66$	1.37×10^{-11}	9.59×10^{-12}
	950	5 ×100 = 500		$Y = -1.36$	1.01×10^{-10}	7.07×10^{-11}
		6 ×100 = 600		$Y = -1.33$	1.23×10^{-10}	8.61×10^{-11}
		7 ×100 = 700		$Y = -1.30$	1.49×10^{-10}	1.043×10^{-10}
0.7	100	5 ×100 = 500	$K_1 = -6$,	$Y = 0.40$	2.11×10^{-6}	1.48×10^{-6}
		6 ×100 = 600	$K_2 = 1$	$Y = 0.55$	4.30×10^{-6}	3.01×10^{-6}

		7 ×100 = 700		$Y = 0.68$	7.8 × 10^{-6}	5.46 × 10^{-6}
	950	5 ×100 = 500		$Y = 1.28$	9.96 × 10^{-5}	6.97 × 10^{-5}
		6 ×100 = 600		$Y = 1.35$	0.00013	9.1 × 10^{-5}
		7 ×100 = 700		$Y = 1.41$	0.00017	1.19 × 10^{-4}
0.7	100	5 ×100 = 500	$K_1 = -6,$ $K_2 = 0.5$	$Y = -2.8$	3.10 × 10^{-15}	2.17 × 10^{-15}
		6 ×100 = 600		$Y = -2.72$	5.82 × 10^{-15}	4.07 × 10^{-15}
		7 ×100 = 700		$Y = -2.66$	9.30 × 10^{-15}	6.51 × 10^{-15}
	950	5 ×100 = 500		$Y = -2.36$	9.20 × 10^{-14}	6.44 × 10^{-14}
		6 ×100 = 600		$Y = -2.33$	1.15 × 10^{-13}	8.05 × 10^{-14}
		7 ×100 = 700		$Y = -2.30$	1.44 × 10^{-13}	1.008 × 10^{-13}