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# Power Distribution Network Expansion and Location Optimization of Additional Facilities: A Case Study

**Urooj Javed [1], Saif Ullah [1], Muhammad Imran [2], Asif Iqbal Malik [3,*] and Nokhaiz Tariq Khan [4]**

1 Department of Industrial Engineering, University of Engineering and Technology, Taxila 47080, Pakistan; uroojeap.hrp@gmail.com (U.J.); saifullah47@yahoo.com (S.U.)
2 Department of Operations and Supply Chain, NUST Business School, National University of Science & Technology, Islamabad 11605, Pakistan; imran.ime13@gmail.com
3 Department of Hotel and Tourism Management, College of Hospitality and Tourism, Sejong University, 209 Neungdong-ro, Gwangjin-gu, Seoul 05006, Korea
4 Department of Business and Management, Information Technology University, Lahore, Pakistan; nokhaiz.tariq@itu.edu.pk
* Correspondence: ai.asifiqbalmalik@gmail.com

**Abstract:** Planning the power distribution network is critical and challenging; the main challenges include the multiple costs involved, selecting the appropriate locations of different nodes of the network at minimal cost, and minimizing the cost of energy loss for both the primary and secondary networks. Literature on the power distribution network presents different approaches, however, lacks to address the several issues of the complex power distribution networks and many aspects are yet to be explored; for example, the uncertain cost of energy loss. This study intends to address the gaps in the literature by proposing a four-phased approach. In doing so, first, an integer linear programming model is formulated with the objective of cost minimization. Secondly, fuzzy variables are used to tackle the parameters with uncertainty; cost of energy loss. In the third phase, a fine-tuned genetic algorithm (FT-GA) that uses the Taguchi Orthogonal Array is introduced to solve the mathematical model. It is worth mentioning that during the design of the experiment, the input parameters are crossover rate, elite count, and population size. In the last phase, a pragmatic approach is adopted and a Pakistan-based case study is used to validate the proposed model and its implication in real-life scenarios. The results exhibit that our proposed approach outperforms traditional methods like the genetic algorithm (GA) and inter-point methods in terms of fitness function value, number of generations, and computational time. This research contributes at both theoretical and managerial levels and may help decision-makers to design networks more efficiently and cost-effectively in Pakistan, Asia, and beyond.

**Keywords:** distribution network expansion; uncertain energy losses; Taguchi Orthogonal array; fine-tuned genetic algorithm; facilities; location-allocation



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## 1. Introduction

Electric power distribution system planning is far more challenging than the power generation itself mainly because of several factors; initial investment cost, maintenance cost, line losses, power losses, and consumer services. Previously, a few reasons behind the energy crisis in Pakistan have been the shortage of electricity, the increasing number of consumers, and fluctuating fuel prices. However, currently, the crisis is mainly due to a low voltage power supply and a poor distribution system. On the other hand, Pakistan needs to move toward renewable resources due to environmental concerns. This creates the need for new types of environmentally friendly power plants and a reengineered distribution networks within the country. In this regard, the government is planning to install renewable plants, including solar and wind plants, to accommodate the energy needs of the country. Designing the new distribution network with new facilities at minimum cost is a challenge.

On one hand, the expansion of the existing power distribution network and inclusion of new power plants, new grid stations, substations in the primary network, and transformers in secondary networks will make the network more complex. Also, the redesign and execution of the new distribution network will have an immense cost. This requires a careful and efficient plan which focuses on high efficiency as well as the minimum cost at the same time. Furthermore, the connection of the main grids with the different number of substations at different locations and the connection with other facilities in the network would be a critical decision due to the huge investment cost of the transmission lines.

Due to previous experiences with poor transmission lines and the cost of maintenance, the government is also concerned about the power losses and the probability of faults occurring in transmission lines. Such a level of complex planning makes it a network optimization problem where there is a dire need to identify the exact size, cost, and location of new power plants, substations, grids, routes, and transmission line branches to connect various facilities in the network. The objective of the network planning is to reduce the overall investment cost of the new facilities, the maintenance cost of the lines and facilities in the network and reduce power losses with maximum customer satisfaction. For example, Figure 1 exhibits the complex nature of an electricity distribution supply chain network design that consists of power plants (p), main grids (g), local grids (h), and transformers (v), and customers (u). Power generation occurs at power plants, which are distributed to main grids, main grids distribute it to local grids, and finally, local grids are connected to transformers and users have connections with the transformers.

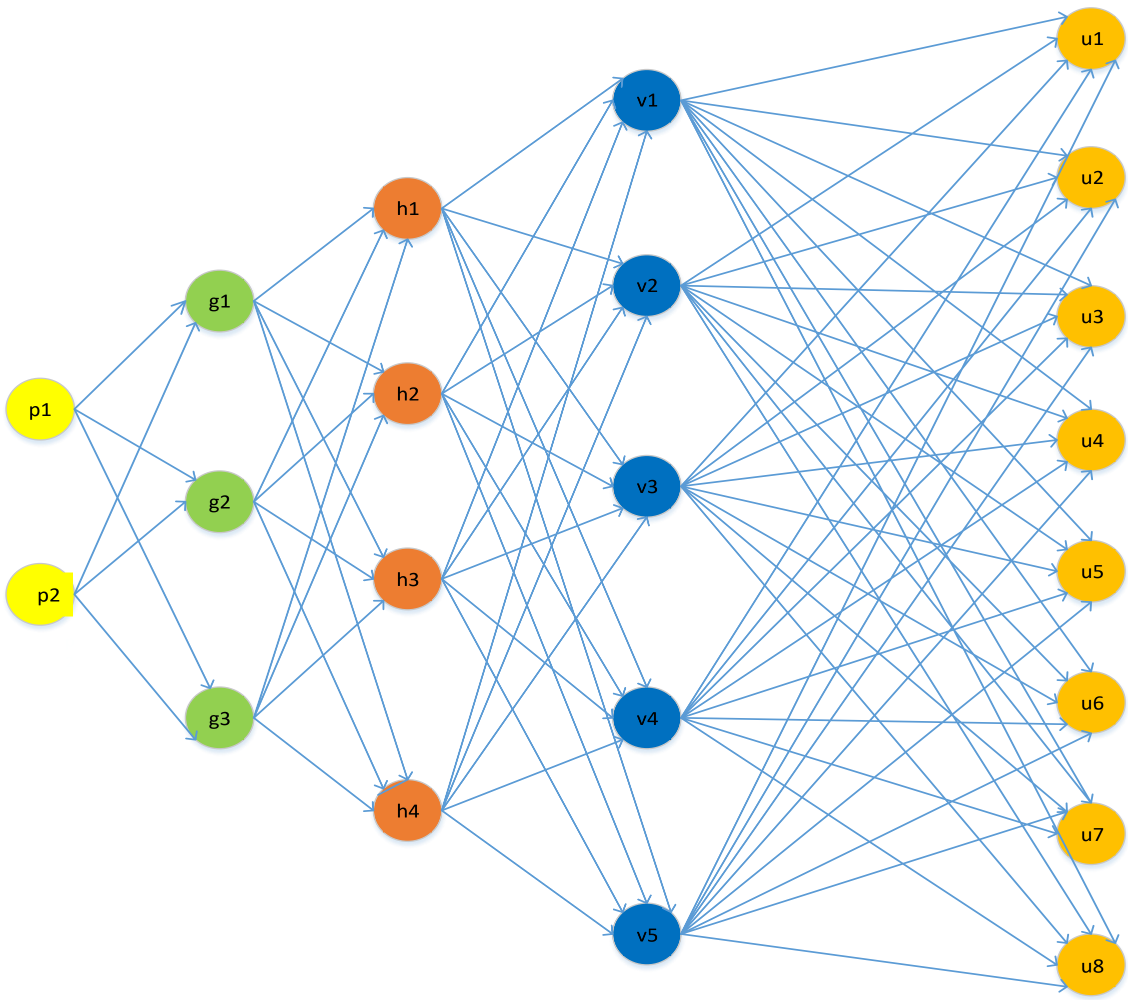


**Figure 1.** Electricity supply chain network.

Based on the government's concerns and the requirement of a new, expanded, and complex distribution network, this research proposes an optimization model that tends to select appropriate locations for plants, main grids, local grids, and transformers to reduce the total cost of installation and maintenance. Further, the model proposes that the decision to connect different power plants with main grids, main grids with local grids, and local grids with transformers is taken by minimizing the line losses as well as cost. This research focuses on the location-allocation of power plants, main grids, local grids, and transformers. In addition, it gives the optimal assignment of transformers to local grids, local grids to main grids, and main grids to the power plants. The objective includes minimizing the total cost, which is composed of fixed installation cost, maintenance cost, and energy costs, where energy cost is assumed to be uncertain during transmission and production. Our model addresses the shortcomings in the previously proposed models, for example, Gonela et al. [1] designed an electricity generation network considering production strategies without taking into account the line losses, decisions for location selection, and assignment of power plants and main grids. Similarly, Bayatloo [2] proposed a two-stage stochastic programming model for electricity supply chain network design by only considering location selection for power plants, main grids, and local grids to minimize the installation cost without considering the energy losses and maintenance in the supply chain network design. This model is an integration of the location-allocation and assignment model for the minimization of energy losses and maintenance cost that differentiate this model from previous literature Chen, Hsu, and Wu [3].

This study proposes a four-phase approach; in the first phase, a mixed-integer linear programming model is formulated that minimizes the total supply chain cost considering uncertain energy losses. In the second phase, the energy loss is regarded as a fuzzy variable in this research as the electricity supply chain networks are too complex and involve large-scale optimization. To optimize the supply chain network design in the third phase, a fine-tuned and hybridized genetic algorithm (GA) is introduced that can solve large optimization in reduced computation time and improved cost value. In the last step, a real case study of the electricity network is proposed. In addition, a set of numerical examples were also solved using other methods such as GA and interior point. Gap analysis is used to assess the solution quality of the proposed algorithm compared to the existing methods.

## 2. Literature Review

Electric power transmission is the mass transmission of electrical energy from its source—for example, a power plant—to an electrical substation where it is consumed [4]. The interconnected lines that carry this transmission are known as transmission lines [5]. However, electric power distribution and transmission lines have always been challenging because of their complex nature, the costs involved in their erection, and the cost of maintenance, and have been the focus of many researchers [6–8]. Mainly, literature on power distribution networks can be segregated into three dimensions; first, most of the researchers focused on the primary networks only [9–16], few focused on secondary [17], and only a few researchers addressed both the primary and secondary networks [18]. The second dimension is the selection of an objective function; for example, Paiva, Khodr, Dominguez-Navarro, Yusta, and Urdaneta [18] selected the investment cost and the cost of energy loss as the objective functions. Whereas Zhao, Wang, Yu, and Chen [15] considered optimal location and size of substations and feeders, and, Nahman and Peric [14] considered the optimal location of feeders in the network with the objective to minimize investment cost and cost of energy loss.

Similarly, Navarro and Rudnick [17] investigated the optimal location and size of substations and feeders with the objective to minimize the cost of investment as well as the cost of energy loss. Lavorato, Rider, Garcia, and Romero [12] and Lotero and Contreras [13] proposed a method to optimize the size and location of substations and feeders with the goal to minimize fixed and variable costs. Several other studies [9–11,13] considered the optimal location and size of substations, feeders, and distributed generation (DGs) to minimize the total cost. The literature shows that a lot of studies have been performed to address DGs for example, Ziari et al. [19] Studied the optimal location and size of substations, feeders, and DGs with the objective to minimize fixed and variable costs. In most of the studies, only the cost is considered as an optimization objective and few studies have taken reliability into consideration while identifying optimal distribution network expansion. Similarly, [20,21] focused on optimizing the size of substations and feeders with the objective to minimize the cost of investment, cost of energy loss with the constraints of voltage drops, which is concerned with reliability.

The installation year of DG in the distribution system has also been considered along with the optimal size and location of DG [22]. Another approach is presented by Gautam and Mithulananthan [23] who worked on optimal placement, including size, to formulate two different objectives, namely, social welfare maximization and profit maximization. Consumer payment, evaluated as a product of location marginal price (LMP) and load at each load bus, is proposed as another ranking to identify candidate nodes for DG placement. Optimal placement and size are identified for social welfare as well as profit maximization problems. Another study was carried out regarding DG in which Celli and Pilo [24] considered the optimal siting and sizing of DG units for a given network so that the cost of power losses during a prefixed period of study can be minimized and investments for grid upgrades can be deferred. The measures used in the literature for energy losses have the limitation that they do not take into consideration the future demand and robustness and flexibility of the network for future needs. The demand is variable and for the future demands of customers, the network is required to be reliable at handling uncertain power demands. For example, Ramírez-Rosado and Bernal-Agustín [25] considered the optimal expansion of an existing distribution system, to meet its forecasted future power demands, determining the optimal sizing and location of future feeders (reserve feeders and operation feeders) and substations, and the optimal feeder reinforcements and/or substitution of the existing feeders, as well as the optimal size increase of the existing substations, with an objective function to reduce economic cost.

The third dimension of the literature reflects the methodology used for optimizing in general and network design in particular. For example, AlRashidi and AlHajri [26] presented an improved particle swarm optimization algorithm (PSO) for the optimal planning of multiple DGs sources. Some studies used Pareto optimization concepts [27–30], especially, Carrano, Soares, Takahashi, Saldanha, and Neto [27] presented a multi-objective approach to optimizing electric distribution networks using a multi-objective genetic algorithm (MO-GA) to get a Pareto solution for their proposed problem. Further, Mendoza, Bernal-Agustin, and Domínguez-Navarro [29] used the Non-Dominated Sorting Genetic Algorithm (NSGA) and Strength Pareto Evolutionary Algorithm (SPEA) for multi-objective optimization and also proposed a fuzzy c-mean clustering algorithm for their considered problem. Moreover, Soroudi and Ehsan [30] considered a multi-objective model for the distribution generation investment with the aim to optimize active losses, costs, and environmental emissions simultaneously to determine the optimal scheme of sizing and sitting of DGs. They obtained Pareto solutions using GA and a fuzzy satisfying method. Also, Cossi, Da Silva, Lazaro, and Mantovani [28] formulated and presented a multi-objective simulated annealing algorithm to solve and get the Pareto results of the proposed problem. On the other hand, Khalesi et al. [31] considered a multi-objective model for DGs to determine the optimal locations to place DGs in the distribution system with the aim to minimize power loss of the system and enhance reliability improvement and voltage profile.

García and Mena [32] used a new evolutionary method called Teaching–Learning Based Optimization (TLBO) algorithm to find the best sites to connect DG systems in a distribution network, choosing among a large number of potential combinations to determine the optimal placement and size of Distributed Generation (DG) units in distribution systems. Fan and Jen [33] introduced enhanced partial search approaches in the particle swarm algorithm to solve optimization problems in the supply chain. Furthermore, most of the literature focused on the existing power distribution models developed is focused on the conventional power generators including diesel units and turbines [34]. However, due to environmental concerns and the shortage of conventional power plants, there is a need to develop models that can consider both types of power generators including conventional and renewable energy power generators, that is, solar power plants and wind turbines. Researchers like Gupta et al. [35] discussed the integration of DGs into the present supply chain and Khatod et al. [36] contributed to handling the uncertainties associated with load and renewable resources (wind and solar) to overcome issues in the continuous supply of power and discussed the optimal placement of photovoltaic arrays (PVAs) and wind turbine generators WTGs in a radial distribution system. Further, Mena et al. [37] proposed a framework for the optimal size and location of the distributed renewable generation units (DG) and also considered the uncertainties in renewable resources availability, components failure and repair events, load and grid power supply. They aimed at simultaneous minimization of the energy not supplied and global cost. Atwa et al. [38] presented a technique for the optimal allocation of different types of renewable distributed generation (DG) units, that is, wind-based DG, solar DG, and biomass DG in the distribution system with the aim to minimize annual energy loss. The global dependence on fossil fuels is dangerous to our environment in terms of their emissions unless specific policies and measures are put in place [39]. Nevertheless, their research reveals that a reduction in the emissions of these gases is possible with the widespread adoption of distributed generation (DG) technologies that feed on renewable energy sources, in the generation of electric power. The main objective of their work is to reduce the harmful effect of the emission of greenhouse gases thus reducing the public concerns over human health risks caused by the conventional method of electricity generation.

In the literature, very little work has been carried out on allocation and assignment simultaneously. For example, García and Mena, Hosseini and Jenab [40] worked on the expansion policy of power plant centers involving the choice of regions that must be allocated to power plant centers and power plant centers capacities over a specified planning horizon (years) were tackled. Nevertheless, in most of the studies, a single objective has been considered for the design of the optimal network. However, in real cases, more than one objective is desired to optimize the network design problems. Fan et al. [41] proposed an algorithm that used the concept of Pareto dominance in multi-objective particle swarm algorithm with empirical-movement diversified-search. Most of the electricity distribution problems are nonlinear in nature and require special metaheuristics. However, the use of metaheuristics requires the management of parameters used in computations. Zahara and Fan [42] introduced a real code genetic algorithm to solve stochastic optimization problems such as energy losses in electricity distribution networks.

In the literature, most of the studies have considered expansion planning in the primary network in terms of multi-objective optimization [17–20]. However, primary and secondary grids are both important in the distribution network expansion and planning to get a global solution. A few research studies have investigated the planning of primary and secondary networks together [18,20,21]. However, they added the costs of primary and secondary grids to make a single objective optimization problem.

A few other studies in the literature [16,19,43–45] considered both primary and secondary networks simultaneously. However, they also optimize the network with the single objective being minimizing the fixed and variable costs. The current research addresses an optimization model for the electricity distribution network. In the electricity distribution network, facilities such as power plants, main grids, local grids are connected with the help of transmission lines. The main objective of the research is to minimize the total cost of installation of new facilities, maintenance cost, and energy loss cost. Energy loss is the function of distance and temperature, so it is considered uncertain in this model. The uncertainty is modeled using fuzzy variables. To solve this integer linear programming issue, a fine-tuned genetic algorithm is used. The fine-tuning is carried out using the Taguchi design of experiments. The consideration of uncertain energy loss in the cost function and the use of Taguchi-based fine-tuned GA differentiate this research from the previous literature.

## 3. Development of Mathematical Model

The objective function is formulated based on the assumptions below and Notation presented in Table 1.

### *3.1. Problem Statement*

Electric power distribution systems are very complex in nature as these may include hundreds of thousands of components: generators, grids, transformers, transmission lines, and customers, etc. The current energy crisis in Pakistan has increased the need for efficient planning and expansion of the power distribution network in the country.

### *3.2. Model Assumptions*

The proposed model is based on the following assumptions:

- The capacity of each power plant, main grid, local grid, and transformer is not the same and is known.
- The maintenance and installation costs of power plants, main grid, local grids, transformers, and transmission lines are known.
- The energy loss cost is assumed to be uncertain and is treated as a fuzzy variable.

### *3.3. Model Notation and Abbreviations*

See Table 1.

**Table 1.** Nomenclature table.

| **Sets** | |
|---|---|
| $p$ | power plants $p = 1, 2, 3, \ldots, P$ |
| $g$ | main grids $g = 1, 2, 3, \ldots, G$ |
| $h$ | local grids $h = 1, 2, 3, \ldots, H$ |
| $v$ | transformers $v = 1, 2, 3, \ldots, V$ |
| $l^p$ | location of power plant "$p$" $l^p = 1, 2, 3, \ldots, L^P$ |
| $l^g$ | location of main grid "$g$" $l^g = 1, 2, 3, \ldots, L^G$ |
| $l^h$ | location of local grid "$h$" $l^h = 1, 2, 3, \ldots, L^H$ |
| $l^v$ | location of transformer "$v$" $l^v = 1, 2, 3, \ldots, L^V$ |
| **Parameters** | |
| $FC_p^{l^p}$ | fixed cost of installation power plant "$p$" at location "$l^p$" |
| $MC_g^{l^g}$ | maintenance cost of main grid "$g$" at location "$l^g$" |
| $FC_g^{l^g}$ | fixed cost of main grid "$g$" at location "$l^g$" |
| $MC_h^{l^h}$ | maintenance cost of local grid "$h$" at location "$l^h$" |
| $FC_h^{l^h}$ | fixed cost of local grid "$h$" at location "$l^h$" |
| $MC_v^{l^v}$ | maintenance cost of transformer "$v$" at location "$l^v$" |
| $MC_{pg}^{l^p l^g}$ | maintenance cost of transmission line between plant "$p$" at location "$l^p$" and main grid "$g$" at location "$l^g$" |
| $FC_{pg}^{l^p l^g}$ | fixed cost of installation of transmission line between "$p$" at location "$l^p$" and main grid "$g$" at location "$l^g$" |
| $MC_{gh}^{l^g l^h}$ | maintenance cost of transmission line between main grid "$g$" at location "$l^g$" and local grid "$h$" at location "$l^h$" |
| $FC_{gh}^{l^g l^h}$ | fixed cost of installation of transmission line between main grid "$g$" at location "$l^g$" and local grid "$h$" at location "$l^h$" |
| $MC_{hv}^{l^h l^v}$ | maintenance cost of transmission line between local grid "$h$" at location "$l^h$" and transformer "$v$" at location "$l^v$" |
| $FC_{hv}^{l^h l^v}$ | fixed cost of installation of transmission line between local grid "$h$" at location "$l^h$" and transformer "$v$" at location "$l^v$" |
| $MC_{vu}^{l^v l^u}$ | maintenance cost of transmission line between transformer "$v$" at location "$l^v$" and users "$u$" at location "$l^u$" |
| $FC_{uv}^{l^v l^u}$ | fixed cost of installation of transmission line between transformer "$v$" at location "$l^v$" and users "$u$" at location "$l^u$" |
| $ELC_{pg}^{l^p l^g}$ | energy loss cost of transmission lines from power plant "$p$" at location "$l^p$" to main grid "$g$" at location "$l^g$" |
| $ELC_{gh}^{l^g l^h}$ | energy loss cost of transmission lines from main grid "$g$" at location "$l^g$" to local grid "$h$" at location "$l^h$" |
| $ELC_{hv}^{l^h l^v}$ | energy loss cost of transmission lines from local grid "$h$" at location "$l^h$" to transformer "$v$" at location "$l^v$" |
| $ELC_{vu}^{l^v l^u}$ | energy loss cost of transmission lines from transformer "$v$" at location "$l^v$" to users "$u$" at location "$l^u$" |

**Table 1.** *Cont.*

| **Decision Variables** |
|---|
| $y_p^{l^p} = \left\{ \begin{array}{ll} 1 & \text{if power plant ``}p\text{'' is installed at location``}l^p\text{''} \\ 0 & \text{otherwise} \end{array} \right\}$ |
| $y_g^{l^g} = \left\{ \begin{array}{ll} 1 & \text{if grid ``}g\text{'' is installed at location``}l^g\text{''} \\ 0 & \text{otherwise} \end{array} \right\}$ |
| $y_h^{l^h} = \left\{ \begin{array}{ll} 1 & \text{if local grid ``}h\text{'' is installed at location``}l^h\text{''} \\ 0 & \text{otherwise} \end{array} \right\}$ |
| $y_v^{l^v} = \left\{ \begin{array}{ll} 1 & \text{if transformer ``}v\text{'' is installed at location``}l^v\text{''} \\ 0 & \text{otherwise} \end{array} \right\}$ |
| $z_{pg}^{l^g l^p} = \left\{ \begin{array}{ll} 1 & \text{if main grid ``}g\text{'' at location ``}l^g\text{'' is connected to the power plant ``}p\text{'' at location ``}l^p\text{''} \\ 0 & \text{otherwise} \end{array} \right\}$ |
| $z_{gh}^{l^h l^g} = \left\{ \begin{array}{ll} 1 & \text{if local grid ``}h\text{'' at location ``}l^h\text{'' is connected to the main grid ``}g\text{'' at location ``}l^g\text{''} \\ 0 & \text{otherwise} \end{array} \right\}$ |
| $z_{hv}^{l^v l^h} = \left\{ \begin{array}{ll} 1 & \text{if transformer ``}v\text{'' at location ``}l^v\text{''is connected to the local grid ``}h\text{'' at location ``}l^h\text{''} \\ 0 & \text{otherwise} \end{array} \right\}$ |

### *3.4. Formulation of Objective Function and Constraints*

Equation (1) is the total cost function in which the first four terms show the maintenance and fixed installation cost, the last three terms indicate maintenance and energy loss cost of transmission lines. It is an integer linear programming model because all decision variables are binary in nature. As a novel approach, the cost of energy loss was considered to be uncertain in the objective function of the model. To model the uncertainty, the cost of energy loss was treated as a fuzzy variable assuming that it follows a trapezoidal membership function. In order to make a variable fuzzy, the crisp input is converted to the fuzzy number [46–49]. Then fuzzy numbers are evaluated using logical rules. Figure 2 describes the fuzzy inference process.

$$\begin{aligned} Minimize\ \ TC = & \sum_{p,l^p=1}^{P,L^p} (MC_p^{l^p} + FC_p^{l^p}) \times y_p^{l^p} + \sum_{g,l^g=1}^{G,L^G} (MC_g^{l^g} + FC_g^{l^g}) \times y_g^{l^g} \\ & + \sum_{h,l^h=1}^{H,L^H} (MC_h^{l^h} + FC_h^{l^h}) \times y_h^{l^h} + \sum_{v,l^v=1}^{V,L^V} (MC_v^{l^v} + FC_v^{l^v}) \times y_v^{l^v} + \\ & \sum_{pg,l^{pg}=1}^{PG,L^pL^G} (MC_{pg}^{l^pl^g} + \widetilde{ELC_{pg}^{l^pl^g}}) \times z_{pg}^{l^pl^g} + \sum_{gh,l^{gh}=1}^{GH,L^GL^H} (MC_{gh}^{l^gl^h} + \widetilde{ELC_{gh}^{l^gl^h}}) \times z_{gh}^{l^gl^h} + \\ & \sum_{hv,l^{hv}=1}^{HV,L^HL^V} (MC_{hv}^{l^hl^v} + \widetilde{ELC_{hv}^{l^hl^v}}) \times z_{hv}^{l^hl^v} \end{aligned} \tag{1}$$

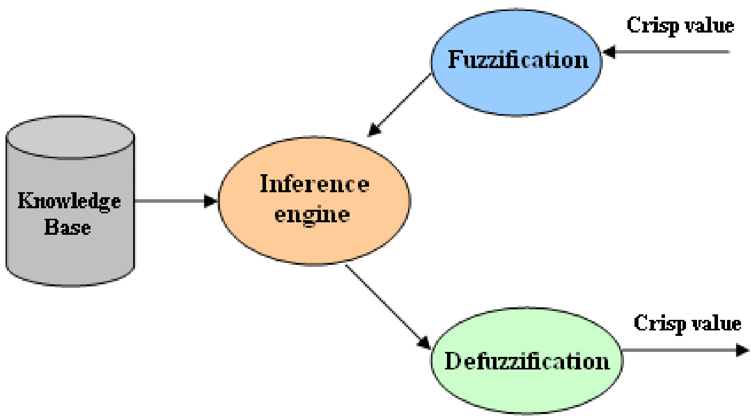


**Figure 2.** Fuzzy inference process.

The final output of fuzzy numbers is a crisp value. In order to convert fuzzy variables in Equation (1), the terms including uncertain parameters were extracted in separate Equations (2)–(4). The center of gravity (COG) method was used to convert these fuzzy numbers into crisp values.

$$M_1 = \sum_{pg,l^{pg}=1}^{PG,L^pL^G} (MC_{pg}^{l^pl^g} + \widetilde{ELC_{pg}^{l^pl^g}}) \times z_{pg}^{l^pl^g} \tag{2}$$

$$M_2 = \sum_{gh,l^{gh}=1}^{GH,L^GL^H} (MC_{gh}^{l^gl^h} + \widetilde{ELC_{gh}^{l^gl^h}}) \times z_{gh}^{l^gl^h} \tag{3}$$

$$M_3 = \sum_{hv,l^{hv}=1}^{HV,L^HL^V} (MC_{hv}^{l^hl^v} + \widetilde{ELC_{hv}^{l^hl^v}}) \times z_{hv}^{l^hl^v} \tag{4}$$

Fuzzification is a three-step process namely, fuzzification, identification of membership function, and finally de-fuzzification using logical rules. In this study, only Equation (2) is used, and the same procedure is repeated for Equations (3) and (4) where Equation (5) shows a trapezoidal membership function.

$$\text{trapezoidal } (x : a, b, c, d) = \left\{ \begin{array}{cc} 0 & x < a \\ \frac{x-a}{b-a} & a \leq x \leq b \\ 1 & b < x < c \\ \frac{d-x}{d-c} & c \leq x \leq d \\ 0 & x > d \end{array} \right\} \tag{5}$$

where, $a$, $b$, $c$, and $d$ are parameters for the trapezoidal membership function and $x$ shows fuzzy variable, which is the cost of energy loss in this case. Considering unit values the Equation (2) reduces to Equation (6) as follows.

$$M_2 = (MC_{gh}^{l^gl^h} + \widetilde{ELC_{gh}^{l^gl^h}}) \times z_{gh}^{l^gl^h} \tag{6}$$

Modifying Equation (6), the value of the cost of energy loss can be computed using Equation (7).

$$ELC_{gh}^{l^gl^h} = \frac{M_2}{z_{gh}^{l^gl^h}} - MC_{gh}^{l^gl^h} \tag{7}$$

To introduce deviational parameters for trapezoidal membership, function the deviation limits can be written as follows in Equations (8)–(10).

$$a = ELC_{gh}^{l^gl^h} - \Delta_1 \tag{8}$$

$$b = ELC_{gh}^{l^gl^h} - \Delta_2 \tag{9}$$

$$c = ELC_{gh}^{l^gl^h} + \Delta_3 \tag{10}$$

$$d = ELC_{gh}^{l^gl^h} + \Delta_4 \tag{11}$$

Putting the values of $a$, $b$, $c$, and $d$ from Equations (8)–(11) to Equation (5) a new Equation (12) is obtained.

$$\text{trapezoidal}\,(x:a,b,c,d)=\left\{\begin{array}{cc} 0 & x<ELC_{gh}^{l^g l^h}-\Delta_1 \\ \frac{x-ELC_{gh}^{l^g l^h}-\Delta_1}{\Delta_2-\Delta_1} & ELC_{gh}^{l^g l^h}-\Delta_1\le x\le ELC_{gh}^{l^g l^h}-\Delta_2 \\ 1 & ELC_{gh}^{l^g l^h}-\Delta_2<x<ELC_{gh}^{l^g l^h}+\Delta_3 \\ \frac{ELC_{gh}^{l^g l^h}+\Delta_4-x}{\Delta_4-\Delta_3} & ELC_{gh}^{l^g l^h}+\Delta_3\le x\le ELC_{gh}^{l^g l^h}+\Delta_4 \\ 0 & x>ELC_{gh}^{l^g l^h}+\Delta_4 \end{array}\right\} \tag{12}$$

As $ELC_{gh}^{l^g l^h}$ is a fuzzy variable and we assume $x=ELC_{gh}^{l^g l^h}$ and then Equation (7) can be written as shown in Equation (13).

$$x=\frac{M_2}{z_{gh}^{l^g l^h}}-MC_{gh}^{l^g l^h} \tag{13}$$

Putting values of Equation (13) to Equation (12), Equation (14) is obtained.

$$\mu_{MC_{gh}^{l^g l^h}}=\left\{\begin{array}{cc} 0 & \frac{M_2}{z_{gh}^{l^g l^h}}-MC_{gh}^{l^g l^h}<ELC_{gh}^{l^g l^h}-\Delta_1 \\ \frac{\frac{M_2}{z_{gh}^{l^g l^h}}-MC_{gh}^{l^g l^h}-ELC_{gh}^{l^g l^h}-\Delta_1}{\Delta_2-\Delta_1} & ELC_{gh}^{l^g l^h}-\Delta_1\le\frac{M_2}{z_{gh}^{l^g l^h}}-MC_{gh}^{l^g l^h}\le ELC_{gh}^{l^g l^h}-\Delta_2 \\ 1 & ELC_{gh}^{l^g l^h}-\Delta_2<\frac{M_2}{z_{gh}^{l^g l^h}}-MC_{gh}^{l^g l^h}<ELC_{gh}^{l^g l^h}+\Delta_3 \\ \frac{ELC_{gh}^{l^g l^h}+\Delta_4-\frac{M_2}{z_{gh}^{l^g l^h}}-MC_{gh}^{l^g l^h}}{\Delta_4-\Delta_3} & ELC_{gh}^{l^g l^h}+\Delta_3\le\frac{M_2}{z_{gh}^{l^g l^h}}-MC_{gh}^{l^g l^h}\le ELC_{gh}^{l^g l^h}+\Delta_4 \\ 0 & \frac{M_2}{z_{gh}^{l^g l^h}}-MC_{gh}^{l^g l^h}>ELC_{gh}^{l^g l^h}+\Delta_4 \end{array}\right\} \tag{14}$$

$$\mu_{MC_{gh}^{l^g l^h}}=\left\{\begin{array}{cc} 0 & \frac{M_2}{z_{gh}^{l^g l^h}}-MC_{gh}^{l^g l^h}<ELC_{gh}^{l^g l^h}-\Delta_1 \\ \frac{\frac{M_2}{z_{gh}^{l^g l^h}}-MC_{gh}^{l^g l^h}-ELC_{gh}^{l^g l^h}-\Delta_1}{\Delta_2-\Delta_1} & \left(ELC_{gh}^{l^g l^h}-\Delta_1+MC_{gh}^{l^g l^h}\right)z_{gh}^{l^g l^h}\le M_2\le\left(ELC_{gh}^{l^g l^h}-\Delta_2+MC_{gh}^{l^g l^h}\right)z_{gh}^{l^g l^h} \\ 1 & \left(ELC_{gh}^{l^g l^h}-\Delta_2+MC_{gh}^{l^g l^h}\right)z_{gh}^{l^g l^h}<M_2<\left(ELC_{gh}^{l^g l^h}+\Delta_3+MC_{gh}^{l^g l^h}\right)z_{gh}^{l^g l^h} \\ \frac{ELC_{gh}^{l^g l^h}+\Delta_4-\frac{M_2}{z_{gh}^{l^g l^h}}-MC_{gh}^{l^g l^h}}{\Delta_4-\Delta_3} & \left(ELC_{gh}^{l^g l^h}+\Delta_3+MC_{gh}^{l^g l^h}\right)z_{gh}^{l^g l^h}\le M_2\le\left(ELC_{gh}^{l^g l^h}+\Delta_4+MC_{gh}^{l^g l^h}\right)z_{gh}^{l^g l^h} \\ 0 & M_2>\left(ELC_{gh}^{l^g l^h}+\Delta_4-MC_{gh}^{l^g l^h}\right)z_{gh}^{l^g l^h} \end{array}\right\} \tag{15}$$

To defuzzify the membership function, the COG method was used. The generic equation for the COG formula is given in Equation (16).

$$M_2=\frac{\int_{-\infty}^{+\infty}\left[(M_2)\mu_{MC_{gh}^{l^g l^h}}(M_2)\right]dM_2}{\int_{-\infty}^{+\infty}\left[\mu_{MC_{gh}^{l^g l^h}}(M_2)\right]dM_2} \tag{16}$$

Using Equations (15) and (16), final crisp Equation (17) can be obtained as shown in Equation (18).

$$M_2=\frac{\begin{array}{c}\left(ELC_{gh}^{l^g l^h}-\Delta_1+MC_{gh}^{l^g l^h}\right)z_{gh}^{l^g l^h}+\left(ELC_{gh}^{l^g l^h}-\Delta_2+MC_{gh}^{l^g l^h}\right)z_{gh}^{l^g l^h}\\ +\left(ELC_{gh}^{l^g l^h}+\Delta_3+MC_{gh}^{l^g l^h}\right)z_{gh}^{l^g l^h}+\left(ELC_{gh}^{l^g l^h}+\Delta_4+MC_{gh}^{l^g l^h}\right)z_{gh}^{l^g l^h}\end{array}}{4} \tag{17}$$

$$M_2=\left(ELC_{gh}^{l^g l^h}+MC_{gh}^{l^g l^h}+\frac{\Delta_3+\Delta_4-\Delta_1-\Delta_2}{4}\right)z_{gh}^{l^g l^h} \tag{18}$$

A similar procedure is repeated for Equations (2) and (4) to get corresponding crisp models as shown in Equations (19) and (20).

$$M_1 = \sum_{pg,l^{pg}=1}^{PG,L^pL^G} \left( MC_{pg}^{l^pl^g} + ELC_{pg}^{l^pl^g} + \frac{\Delta_3 + \Delta_4 - \Delta_1 - \Delta_2}{4} \right) \times z_{pg}^{l^pl^g} \tag{19}$$

$$M_3 = \sum_{hv,l^{hv}=1}^{HV,L^HL^V} \left( MC_{hv}^{l^hl^v} + ELC_{hv}^{l^hl^v} + \frac{\Delta_3 + \Delta_4 - \Delta_1 - \Delta_2}{4} \right) \times z_{hv}^{l^hl^v} \tag{20}$$

Adding values from Equations (18) and (19), the final objective function from Equation (1) will change to Equation (21), which is now a crisp model and can be solved using optimization approaches.

$$\begin{aligned} Minimize\ TC =& \sum_{p,l^p=1}^{P,L^p} (MC_p^{l^p} + FC_p^{l^p}) \times y_p^{l^p} + \sum_{g,l^g=1}^{G,L^G} (MC_g^{l^g} + FC_g^{l^g}) \times y_g^{l^g} \\ &+ \sum_{h,l^h=1}^{H,L^H} (MC_h^{l^h} + FC_h^{l^h}) \times y_h^{l^h} + \sum_{v,l^v=1}^{V,L^V} (MC_v^{l^v} + FC_v^{l^v}) \times y_v^{l^v} + \\ &\sum_{pg,l^{pg}=1}^{PG,L^pL^G} (MC_{pg}^{l^pl^g} + ELC_{pg}^{l^pl^g} + \tfrac{\Delta_3+\Delta_4-\Delta_1-\Delta_2}{4}) \times z_{pg}^{l^pl^g} + \\ &\sum_{gh,l^{gh}=1}^{GH,L^GL^H} (MC_{gh}^{l^gl^h} + ELC_{gh}^{l^gl^h} + \tfrac{\Delta_3+\Delta_4-\Delta_1-\Delta_2}{4}) \times z_{gh}^{l^gl^h} + \\ &\sum_{hv,l^{hv}=1}^{HV,L^HL^V} (MC_{hv}^{l^hl^v} + ELC_{hv}^{l^hl^v} + \tfrac{\Delta_3+\Delta_4-\Delta_1-\Delta_2}{4}) \times z_{hv}^{l^hl^v} \end{aligned} \tag{21}$$

***Constraints***

The constraint in Equation (22) shows that a power plant will be assigned only one location.

$$\sum_{p=1}^{P} y_p^{lp} = 1 \qquad \forall_{lp} \tag{22}$$

Constraints in Equation (23) depicts that at one location only one plant can be installed.

$$\sum_{l^p=1}^{L^p} y_p^{lp} = 1 \qquad \forall_p \tag{23}$$

Constraints presented in Equations (24) and (25) are assignment constraints for different main grids at different locations

$$\sum_{g=1}^{G} y_g^{\mathrm{lg}} = 1 \qquad \forall_{\mathrm{lg}} \tag{24}$$

$$\sum_{l^g=1}^{L^g} y_g^{\mathrm{lg}} = 1 \qquad \forall_g \tag{25}$$

Constraints in Equations (26) and (27) show the assignment constraints for different local grids at different locations.

$$\sum_{h=1}^{H} y_h^{\mathrm{l}h} = 1 \qquad \forall_{\mathrm{l}h} \tag{26}$$

$$\sum_{l^h=1}^{L^h} y_h^{\mathrm{l}h} = 1 \qquad \forall_h \tag{27}$$

Constraints in Equations (28) and (29) show the assignment constraints for transformers at different locations.

$$\sum_{v=1}^{V} y_v^{lv} = 1 \qquad \forall_{lv} \tag{28}$$

$$\sum_{l^v=1}^{L^v} y_v^{lv} = 1 \qquad \forall_{v} \tag{29}$$

Constraints in Equations (30) and (31) show the connection allocation of main grid to the power plants.

$$\sum_{g,p=1}^{L^g,L^p} z_{gp}^{l^g l^p} = y_p^{l^p} \qquad \forall_{l^g} \quad \forall_{l^p} \tag{30}$$

$$\sum_{g,p=1}^{L^g,L^p} z_{gp}^{l^g l^p} = y_g^{l^g} \qquad \forall_{l^g} \quad \forall_{l^p} \tag{31}$$

Constraints in Equations (32) and (33) show the connection allocation of local grid to main grid.

$$\sum_{h,g=1}^{L^h,L^g} z_{hg}^{l^h l^g} = y_g^{l^g} \qquad \forall_{l^h} \quad \forall_{l^g} \tag{32}$$

$$\sum_{h,g=1}^{L^h,L^g} z_{hg}^{l^h l^g} = y_h^{l^h} \qquad \forall_{l^h} \quad \forall_{l^g} \tag{33}$$

Constraints in Equations (34) and (35) show the allocation of local grids to the transformers at different locations.

$$\sum_{h,v=1}^{L^h,L^v} z_{hv}^{l^g l^v} = y_h^{l^h} \qquad \forall_{l^h} \quad \forall_{l^v} \tag{34}$$

$$\sum_{h,v=1}^{L^h,L^v} z_{hv}^{l^g l^v} = y_v^{l^v} \qquad \forall_{l^h} \quad \forall_{l^v} \tag{35}$$

Non-negativity constraints are given in Equations (36)–(42)

$$0 \leq y_p^{l^p} \leq 1 \tag{36}$$

$$0 \leq y_g^{l^g} \leq 1 \tag{37}$$

$$0 \leq y_h^{l^h} \leq 1 \tag{38}$$

$$0 \leq y_v^{l^v} \leq 1 \tag{39}$$

$$0 \leq z_{gp}^{l^g l^p} \leq 1 \tag{40}$$

$$0 \leq z_{ph}^{l^p l^h} \leq 1 \tag{41}$$

$$0 \leq z_{hv}^{l^h l^v} \leq 1 \tag{42}$$

All decision variables in this problem are binary. Therefore, this model is treated as an integer linear programming model.

## 4. Research Methodology

*Fine-Tuned Genetic Algorithm (FT-GA)*

The performance of the GA varies from problem to problem, and it also depends on the nature of the problem such as in non-deterministic polynomial (NP) hard and nonlinear programming models [50]. GA is a metaheuristic, and its performance depends on various parameters such as crossover, mutation rate, selection method, population size, and the number of generations. Different strategies have been introduced in the literature to improve the performance of GA. The use of the Taguchi Orthogonal array is most popular for improving the performance of GA in terms of computational time, the number of generations, and objective function value. In this research, mutation rate, crossover rate, population size was used as controlling factors and their values have three levels. Table 2 represents the factors and their levels.

**Table 2.** Factors and levels for FT-GA.

| Factor | Levels | | |
|---|---|---|---|
| | **−1** | **0** | **+1** |
| Elite count | 20 | 40 | 60 |
| Crossover rate | 0.2 | 0.4 | 0.6 |
| Population size | 100 | 200 | 300 |

Using factors and their levels from Table 2, a Taguchi orthogonal array L27 was chosen for this experiment in which responses are computational time, the number of generations, and the fitness function value of the objective function. The reason behind the selection of orthogonal array L27 was to solve the same problem 27 times with different parametric configurations. The signal-to-noise ratio was used to find the optimal parameters for the genetic algorithm. Equation (43) shows the signal-to-noise ratio.

$$S/N = -10 \log \sum \left( \frac{Y}{n} \right) \quad (43)$$

The responses need to be minimized so a smaller value is chosen as an optimal value of parameters for the genetic algorithm. Other algorithms, such as GA (without fine-tuning) and interior point, were used to solve the same problem, and their relative efficiency with respect to fined tuned GA was evaluated using Equation (44).

Relative performance deviations (RPD) were computed using the following formula in Equation (44).

$$\mathrm{Rel}ative\ Performance\ Deviation = \frac{Algorithm_{sol} - Best_{sol}}{Best_{sol}} \quad (44)$$

RPDs were calculated for each algorithm. Figure 3 shows the flow diagram and the steps required to carry out the computations of the proposed FT-GA. As a first step, a random population was generated in which each individual was a potential solution to the problem. Second, parameters such as mutation, crossover rate, and population size were set. Next, the evaluation of each individual was performed. The fitness function value was calculated and the fittest individuals were selected. Crossover and mutation operators were used to bring more diversity in the results and to improve the convergence point of the algorithm. However, the selection of the values of the parameters was done using the Taguchi Orthogonal array. The best values of these parameters were used in the algorithm to get the best results in terms of computational time, the number of generations, and fitness function values.

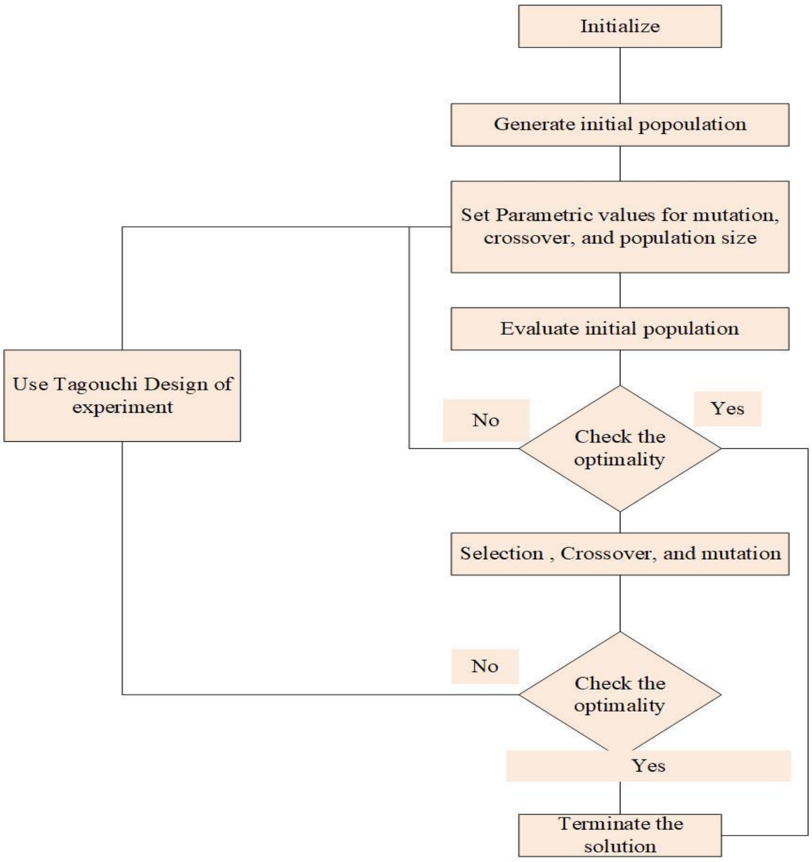


**Figure 3.** Proposed fine-tuned genetic algorithm.

A chromosome in GA is a potential solution to the problem that highlights the initial values. Unlike traditional optimization approaches, in GA, an initial solution to the problem is generated randomly considering the constraints in the problem, if any. The structure of the chromosome can be real coded as well as binary coded. When real coded, the genes in the chromosome are either numbers or objects, however, in the case of a binary chromosome structure the values of decision variables are in the form of 0 or 1 (binary form). The binary structure of a chromosome can be unidirectional, bi-directional, or multi-directional. Figure 4 shows the structure of the components of chromosomes.

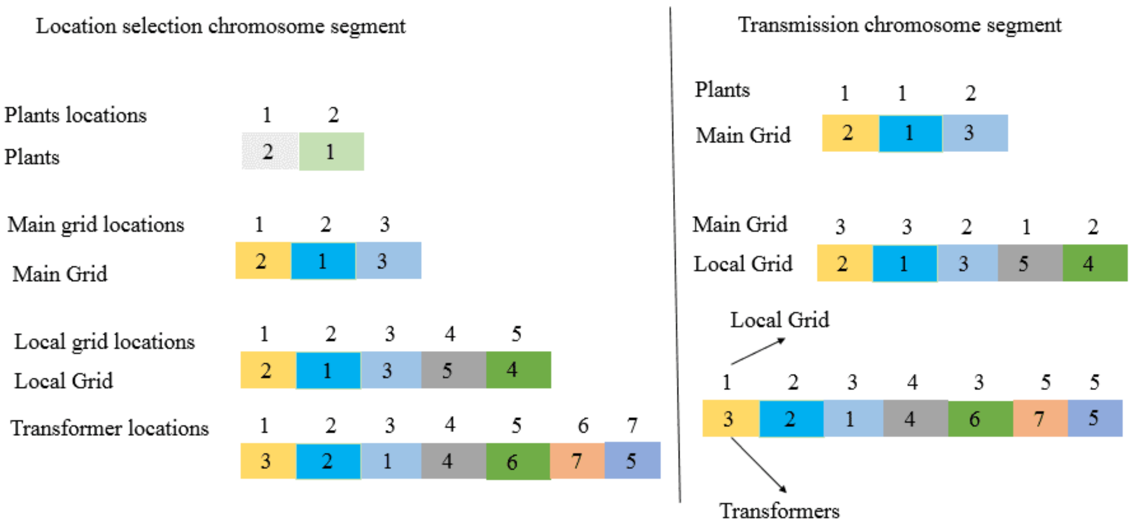


**Figure 4.** Real coded chromosome structure in segments.

All segments of the chromosomes from Figure 4 can be combined into a single structure as shown in Figure 5. The main objective of the decomposition of chromosomes is to increase the clarity of the chromosome structure because its binary equivalent form will be too complex. The real coded chromosome is changed to a binary coded chromosome and this process is called encoding. The reason for encoding is to improve the computational power of the solvers because of the involvement of binary variables. GA is a metaheuristic process and generation/iteration continues until the optimal point is achieved. Crossover and mutation are two operators used for bringing diversity in the evaluation process of the fitness function. In this research, for constraint optimization, the constraint-dependent crossover is used. The objective to use such an approach is to ensure constraint satisfaction through an iterative process. In the crossover, two parent chromosomes crossover together to generate child chromosomes. In the reproduction process, there is an exchange of genes between two parent chromosomes. Figure 6 shows the crossover of chromosomes for this optimization problem.

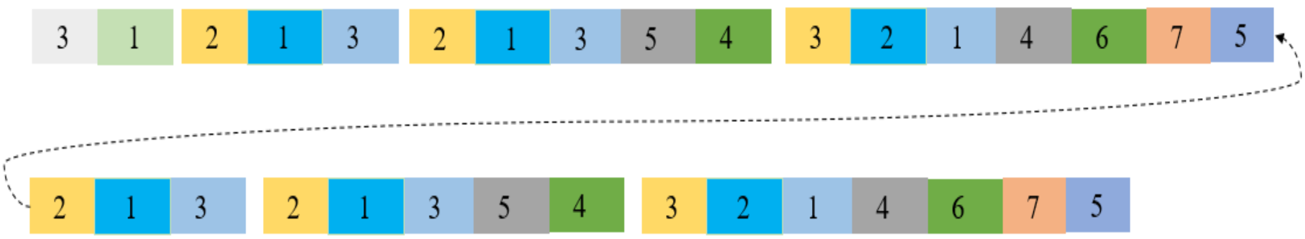

**Figure 5.** Combined real coded chromosome structure in segments.

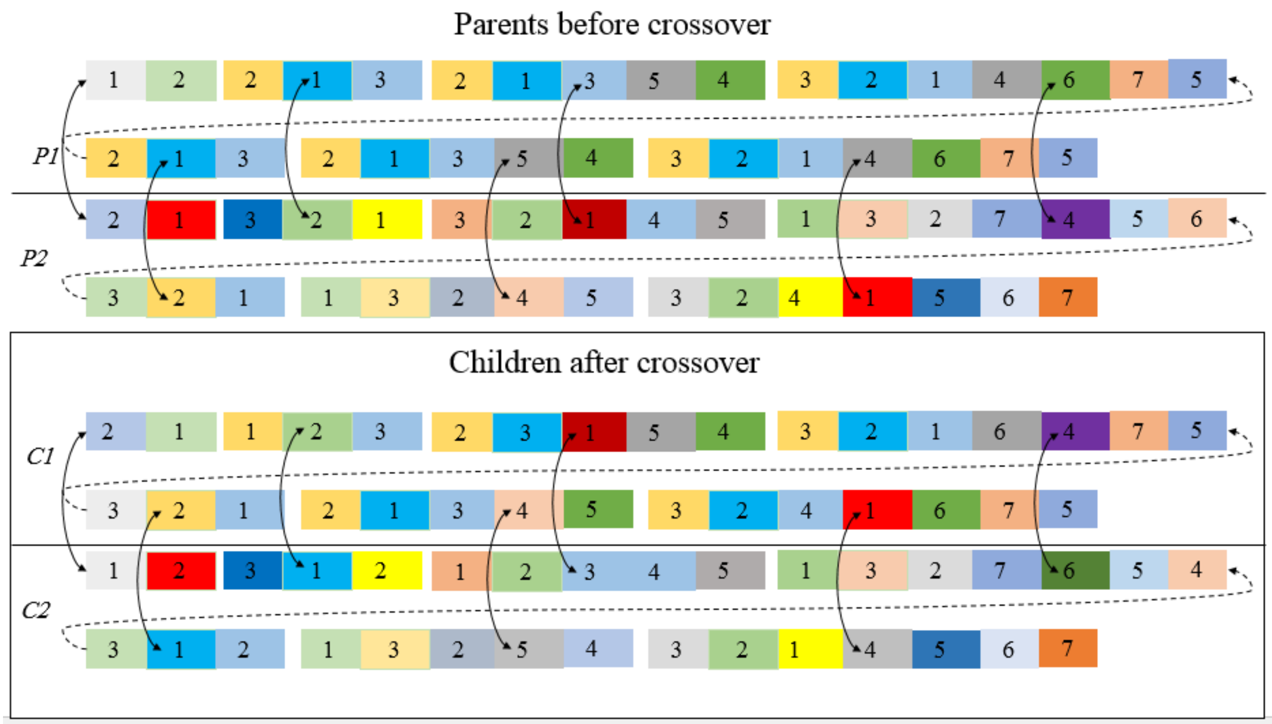


**Figure 6.** Constraint-dependent crossover.

Mutation is another genetic operator in GA for introducing diversity in the evaluation process. Mutations are the self-changes within the chromosomes and this process continues in successive generations until the convergence point is reached. Figure 7 shows the mutation process for this optimization process. The step-by-step implementation of the proposed methodology is shown in Table 3.

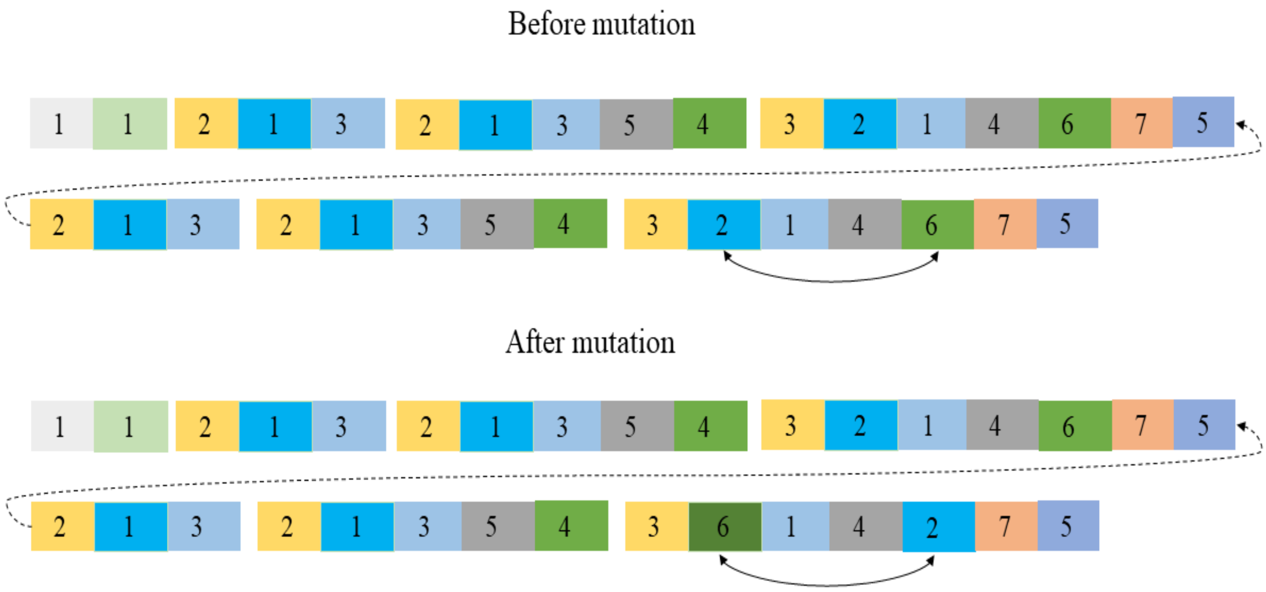


**Figure 7.** Illustration of mutation process.

**Table 3.** Fine Tuned Genetic Algorithm.

| | |
|---|---|
| Step 1: | Identify the controlling parameters of the genetic algorithm<br>Define the factors (GA parameters) and their levels<br>Identify the design of the experiment and create a set of experiments |
| Step 2: | Formulate the objective function/constraint and initialize GA<br>Initialize genetic algorithm<br>Create a set of GAs with different configurations of parameters<br>Run GA for all experiments and compute cost, CPU time, and number of generations |
| Step 3: | Evaluate the quality of the solution<br>Normalize cost, CPU time, and number of generations<br>Add normalized values to get a single response<br>Use the signal-to-noise ratio to get the best solution with optimal parameters of GA |
| Step 4: | Use optimal GA configuration for solving other problems |

## 5. Case Study

To further elaborate on the usefulness of the proposed decision support system for electricity distribution, a case study of the Government of Khyber Pakhtoon Khan (KPK) is presented in this section. Data were collected from various department websites of the KPK government.

### *Problem Statement for Case Study*

In KPK, currently, 10 hydropower plants are operating at different locations, the details of which are highlighted on Google Maps in Figure 8. To meet the demand for electricity in KPK, the KPK government is planning to install two new plants of different capacities at Nowshera and Mardan. The installation cost of power plants varies based on the capacity and location of the plant.

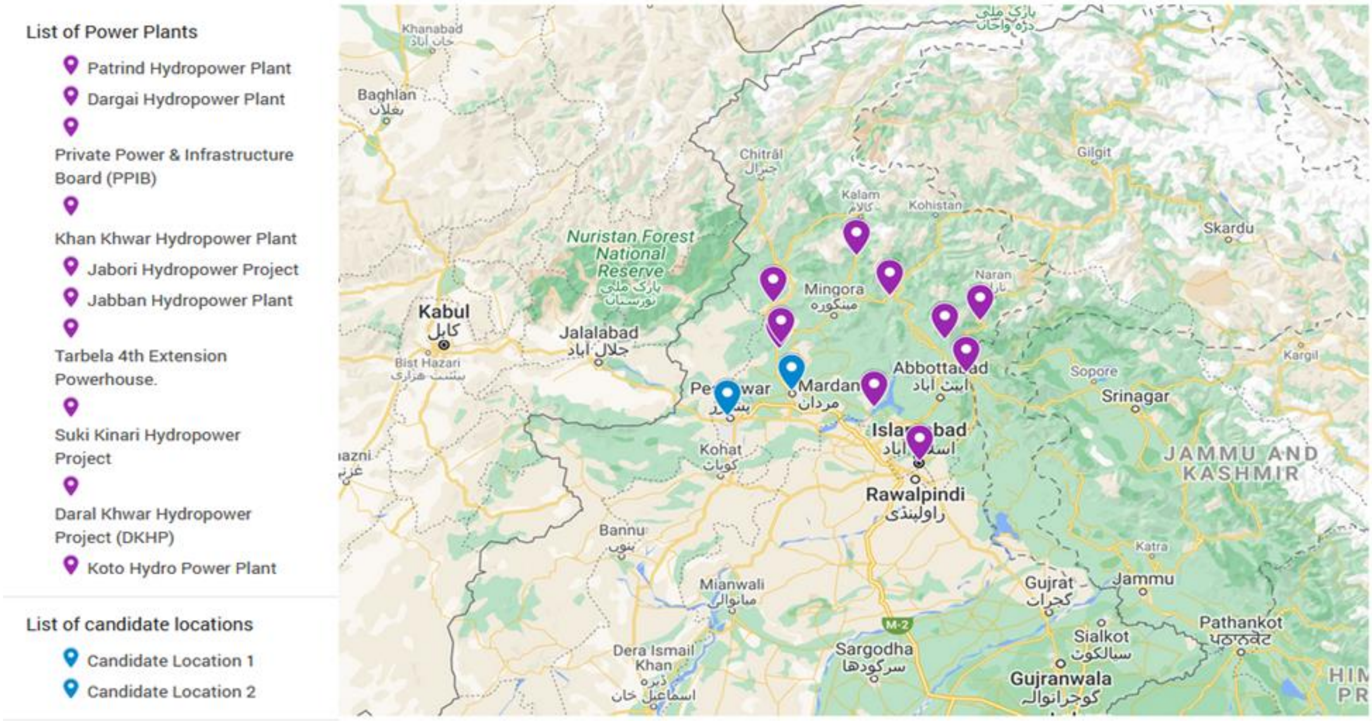


**Figure 8.** List of power plants in KPK and candidate locations for new plants.

Table 4 shows the installation cost of two new plants at two candidate locations namely Peshawar and Mardan. The data are estimated from the web source of the National Hydropower Association (NHA) [51]. It is estimated that Pakistan has 60,000 MW of hydropower potential and currently only 7320 MW is being produced. According to the NHA, the installation cost is USD 1000–5000. However, to simplify, the average value of USD 3000 per KW hour was used in this study [51]. In addition to installation cost, the infrastructure establishment cost was considered that varies from location to location. Note that data used in this study are estimated and there are chances of variation from actual installation, maintenance, and energy loss costs.

**Table 4.** Fixed installation cost in millions (USD) of main power plants at candidate location.

| Location | Plant Type 1 (300 MW) (1 MW = 1000 KW) | Plant Type 2 (400 MW) (1 MW = 10,000 KW) |
|---|---|---|
| Peshawar | 250 | 290 |
| Mardan | 276 | 315 |

It is very difficult to compute the maintenance cost. However, according to a report by the "Energy Technology System Analysis Program", it is estimated that the maintenance cost is about 1.5% of the total installation cost [52]. Similarly, to expand the electricity network, the KPK government is also planning to install three new main grids at three different locations namely Dir, Kamra, and Haripur (see Figure 9).

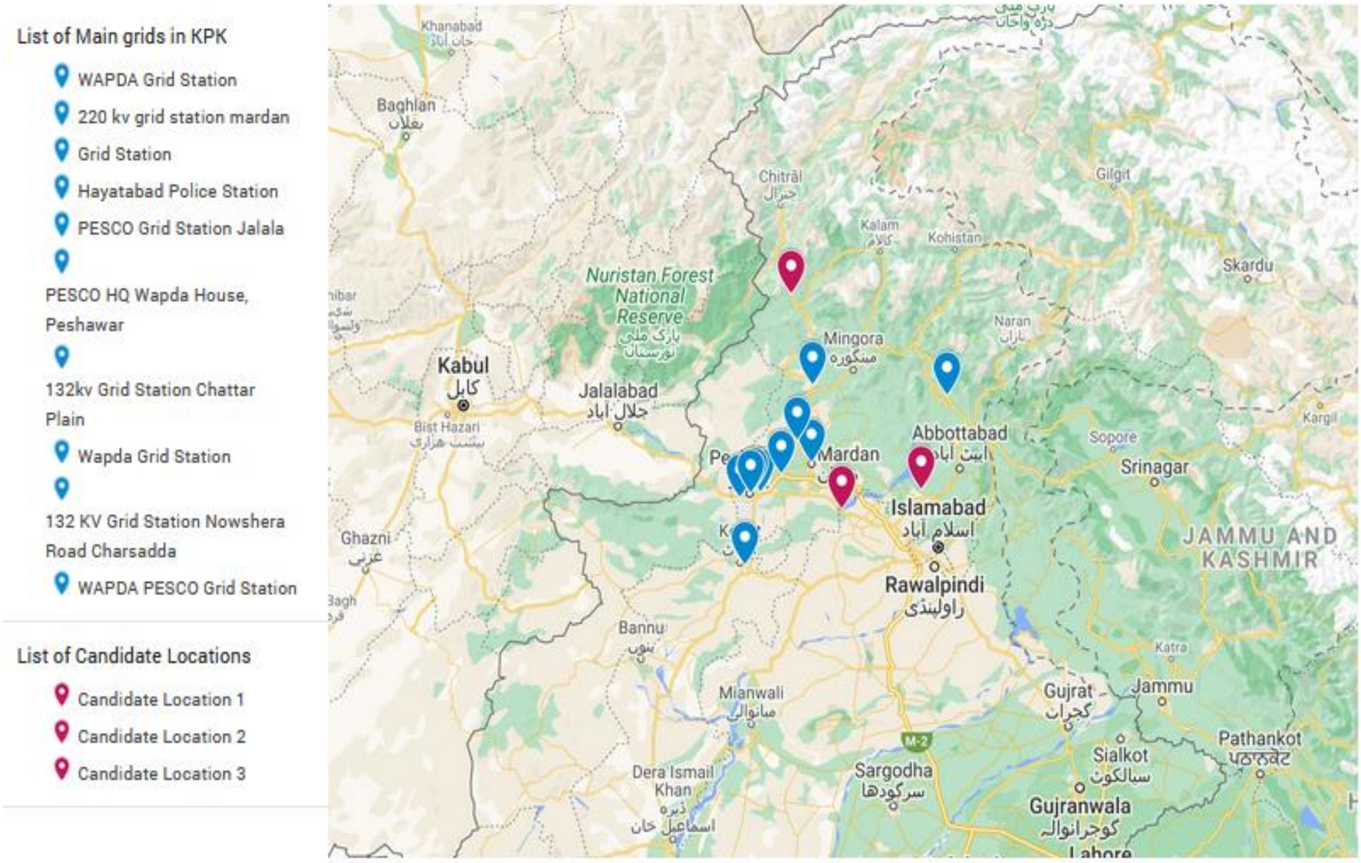


**Figure 9.** List of main grids in KPK and candidate locations for new main grids.

The estimated installation of main grids is given in Table 5. Note that it is almost difficult to calculate installation costs because of the purchase of electrical appliances and their installation. In this study, it was assumed that the maintenance cost of the main grid is 0.9% of the total installation cost of the main grid [52].

**Table 5.** Fixed installation cost in millions (USD) of main grids at candidate locations.

| | Main Grid Type 1 | Main Grid Type 2 | Main Grid Type 3 |
|---|---|---|---|
| Dir | 110 | 115 | 118 |
| Kamra | 113 | 116 | 109 |
| Haripur | 115 | 119 | 104 |

In addition to the main grid, KPK is also planning to install five local grids that will be connected to the transformers in different regions. Figure 10 shows the location of existing local grids and candidate locations of new local grids.

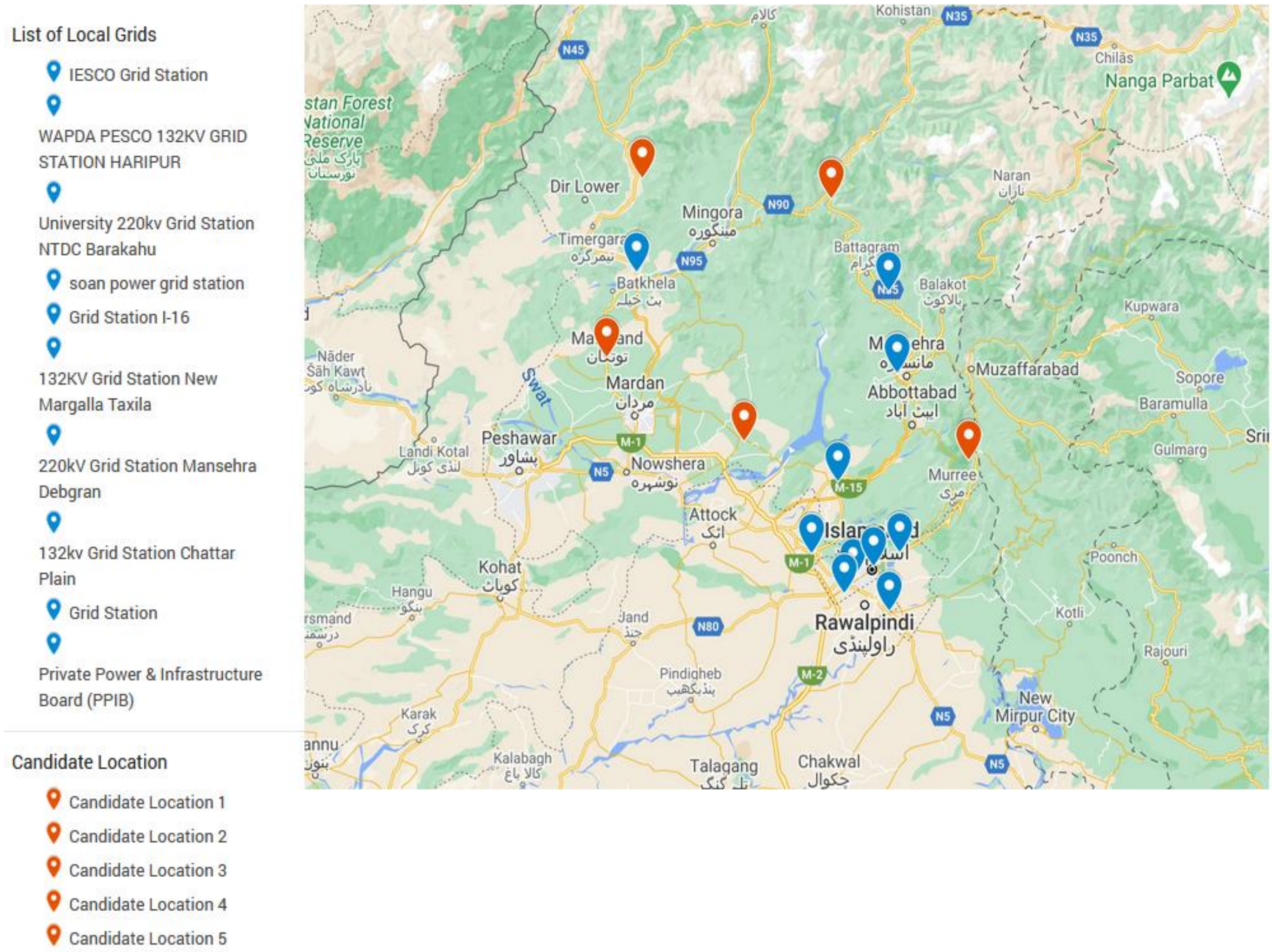


**Figure 10.** List of local grids in KPK and candidate locations for local grids.

In an electricity distribution network, local grids are connected to transformers. The transformers are then further connected to the end-users. As the number of transformers in KPK is very high, just to limit the study in this research, only seven transformers were considered and highlighted on Google Maps, as can be seen in Figure 11. The maintenance cost of local grids is 0.78% of the total fixed installation cost [52]. The fixed installation costs of local grids at different locations are provided in Table 6.

**Table 6.** Fixed installation cost in millions (USD) of local grids at different locations.

| | Local Grid Type 1 | Local Grid Type 2 | Local Grid Type 3 | Local Grid Type 4 | Local Grid Type 5 |
|---|---|---|---|---|---|
| Basham | 48 | 56 | 59 | 43 | 35 |
| Vari-Dir Bala | 58 | 30 | 20 | 21 | 45 |
| Hathian | 48 | 25 | 27 | 31 | 50 |
| Swabi | 20 | 55 | 45 | 53 | 58 |
| Nathiagli | 40 | 58 | 24 | 36 | 55 |

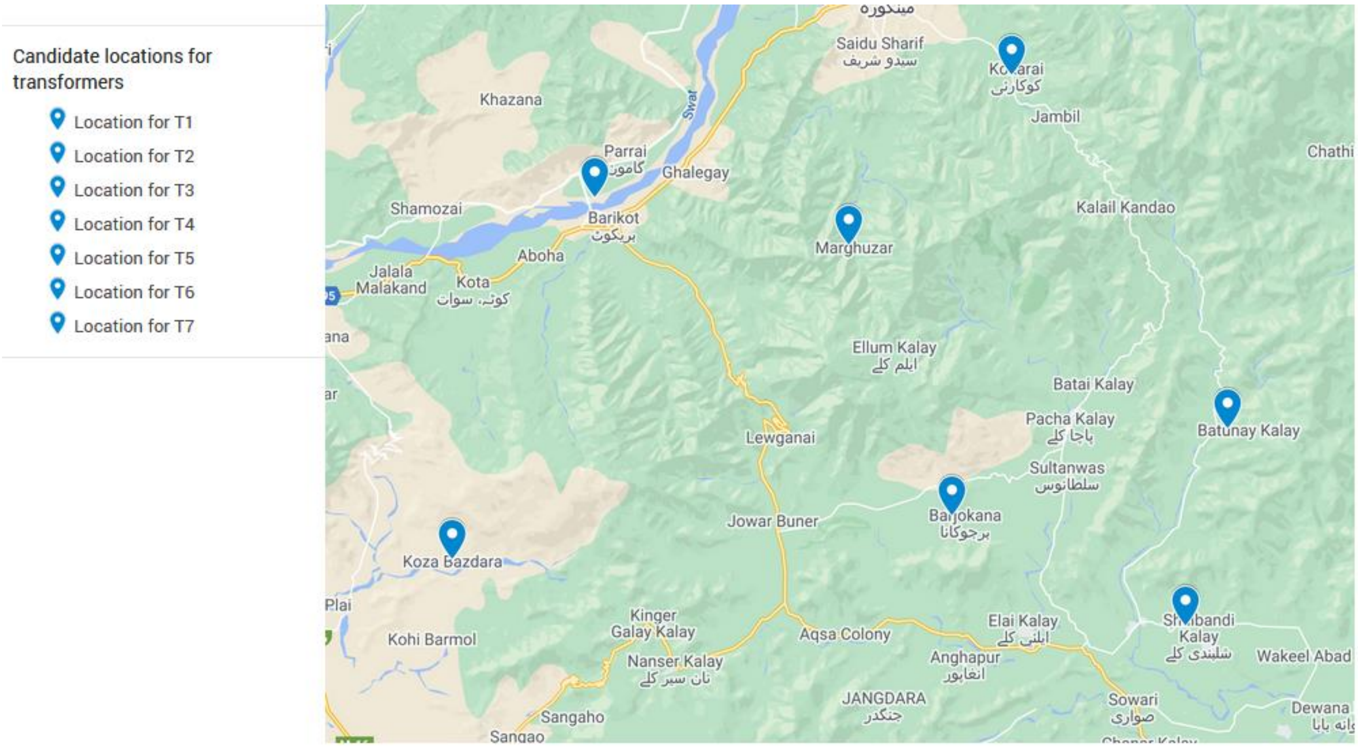


**Figure 11.** Candidate locations for transformers.

The fixed installation cost of each transformer is given in Table 7. The maintenance cost of transformers is 0.45% of the total installation cost [52].

**Table 7.** Fixed installation cost in millions (USD) of each type of transformer at each location.

| | Trans Type 1 | Trans Type 2 | Trans Type 3 | Trans Type 4 | Trans Type 5 | Trans Type 6 | Trans Type 7 |
|---|---|---|---|---|---|---|---|
| Koza Bazdara | 0.222 | 0.121 | 0.440 | 0.211 | 0.394 | 0.030 | 0.382 |
| Barjokana | 0.041 | 0.080 | 0.276 | 0.356 | 0.151 | 0.451 | 0.454 |
| Shalbandi Kalay | 0.157 | 0.208 | 0.409 | 0.267 | 0.404 | 0.070 | 0.112 |
| Batunay Kalay | 0.436 | 0.276 | 0.297 | 0.482 | 0.092 | 0.112 | 0.107 |
| Kokarai | 0.339 | 0.206 | 0.181 | 0.312 | 0.408 | 0.380 | 0.399 |
| Marghuzar | 0.264 | 0.203 | 0.292 | 0.340 | 0.103 | 0.117 | 0.352 |
| Barikot | 0.051 | 0.440 | 0.166 | 0.341 | 0.261 | 0.108 | 0.447 |

Power plants, main grids, and local grids are interconnected with each other with the help of transmission lines. The KPK government is interested in connecting power plants to main grids, main grids to local grids, and local grids to transformers in such a way that energy loss would be minimized during the transmission of electricity. The energy loss cost in the transmission line is USD 150 per kilometer and the maintenance cost per kilometer is USD 90. The distances between power plants and main grids, and from main grids to local grids, and from local grids to transformers are given in Tables 8–10. Note that this distance is a straight-line distance directly calculated from Google Maps.

**Table 8.** Straight line distance between power plant and main grids (km).

| | Dir | Kamra | Haripur |
|---|---|---|---|
| Peshawar | 133 | 76 | 124 |
| Mardan | 109 | 51 | 100 |

**Table 9.** Straight line distance between main grid and local grids (km).

| | Basham | Vari-Dir Bala | Hathian | Swabi | Nathiagli |
|---|---|---|---|---|---|
| Dir | 90 | 25 | 86 | 125 | 185 |
| Kamra | 125 | 127 | 75 | 30 | 93 |
| Haripur | 102 | 140 | 103 | 43 | 40 |

**Table 10.** Straight line distance between main grid and local grids (km).

| | Koza Bazdara | Barjokana | Shalbandi Kalay | Batunay Kalay | Kokarai | Marghuzar | Barikot |
|---|---|---|---|---|---|---|---|
| Basham | 78 | 56 | 56 | 47 | 44 | 54 | 66 |
| Vari-Dir Bala | 52 | 57 | 67 | 64 | 43 | 108 | 36 |
| Hathian | 27 | 47 | 57 | 61 | 61 | 64 | 44 |
| Swabi | 56 | 48 | 43 | 51 | 68 | 7 | 66 |
| Nathiagli | 127 | 103 | 92 | 91 | 116 | 77 | 126 |

## 6. Results and Discussion

To solve the problem, an L27 Taguchi Orthogonal array was generated in which mutation rate, crossover rate, and population size were the input factors. Fitness function values, number of generations, and computational time were considered as response variables. Table 11 shows the design of the experiment along with its responses. To complete Table 11, GA was run at different configurations as suggested by the design of experiments and their responses were recorded.

**Table 11.** L27 Design of experiment and responses.

| | Input Factors | | | Responses | | |
|---|---|---|---|---|---|---|
| Exp # | Elite Count | Mutation Rate | Population Size | Fitness Function | Generation | CPU Time |
| 1 | 20 | 0.2 | 100 | 2654.20 | 112 | 12.55 |
| 2 | 20 | 0.2 | 100 | 2724.40 | 118 | 14.05 |
| 3 | 20 | 0.2 | 100 | 2714.20 | 124 | 13.32 |
| 4 | 20 | 0.4 | 200 | 2657.90 | 143 | 16.06 |
| 5 | 20 | 0.4 | 200 | 2630.20 | 150 | 25.73 |
| 6 | 20 | 0.4 | 200 | 2683.00 | 141 | 27.03 |
| 7 | 20 | 0.6 | 300 | 2647.40 | 178 | 41.72 |
| 8 | 20 | 0.6 | 300 | 2624.20 | 177 | 39.53 |
| 9 | 20 | 0.6 | 300 | 2640.60 | 184 | 42.96 |
| 10 | 40 | 0.2 | 200 | 2673.70 | 155 | 20.80 |
| 11 | 40 | 0.2 | 200 | 2633.50 | 151 | 20.15 |
| 12 | 40 | 0.2 | 200 | 2674.20 | 147 | 19.66 |
| 13 | 40 | 0.4 | 300 | 2666.50 | 168 | 37.97 |
| 14 | 40 | 0.4 | 300 | 2640.50 | 166 | 36.59 |
| 15 | 40 | 0.4 | 300 | 2661.90 | 176 | 40.80 |
| 16 | 40 | 0.6 | 100 | 2678.10 | 155 | 14.69 |
| 17 | 40 | 0.6 | 100 | 2658.30 | 152 | 11.81 |
| 18 | 40 | 0.6 | 100 | 2660.30 | 143 | 12.73 |
| 19 | 60 | 0.2 | 300 | 2659.70 | 159 | 33.61 |
| 20 | 60 | 0.2 | 300 | 2673.00 | 154 | 30.85 |
| 21 | 60 | 0.2 | 300 | 2633.40 | 155 | 32.18 |
| 22 | 60 | 0.4 | 100 | 2652.10 | 145 | 9.61 |
| 23 | 60 | 0.4 | 100 | 2686.30 | 157 | 11.48 |
| 24 | 60 | 0.4 | 100 | 2673.70 | 165 | 11.60 |
| 25 | 60 | 0.6 | 200 | 2629.10 | 174 | 27.92 |
| 26 | 60 | 0.6 | 200 | 2667.00 | 175 | 26.11 |
| 27 | 60 | 0.6 | 200 | 2654.10 | 174 | 30.08 |

MINITAB software was used to find the signal-to-noise ratio and the results are displayed in Figure 12, indicating a 0.2 crossover rate, 20% elite count, and 100 population size gives better results and these parameters are the optimal parameters for Fine-Tuned Genetic Algorithm.

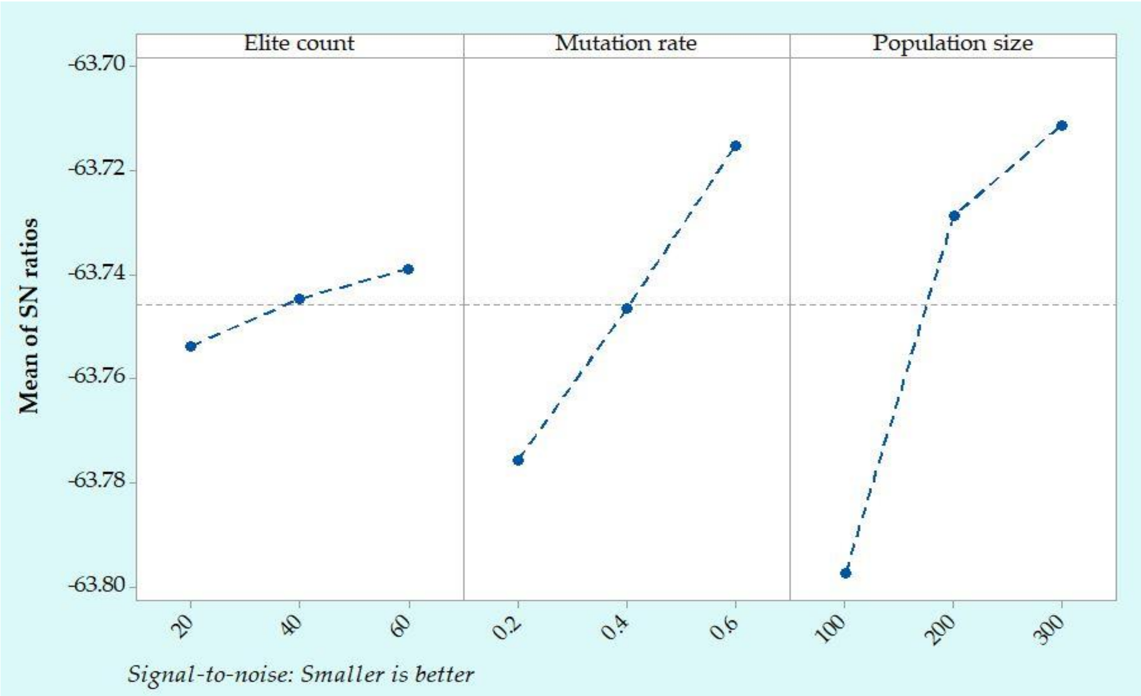


**Figure 12.** Signal-to-noise ratios: smaller is better.

All responses need to be minimized, so smaller is better $S/N$ as shown in Equation (43). To solve the problem with the fine-tuned genetic algorithm, the optimal configurations, that is, 20% elite count, 0.2 crossover rate, and 100 population size were used.

### *6.1. Optimal Solution for Case Study*

The design of the experiments was created using MINITAB software and all experiments and final optimization using fine-tuned GA was implemented on MATLAB and computations were carried out using a personal computer with a 2GHz processor, 8 GB RAM, and Core i7. Table 12 shows the best cost achieved from fined-tuned GA.

**Table 12.** Optimal results.

| | Cost in Millions (USD) | Number of Generation | CPU (Seconds) |
|---|---|---|---|
| Values | 2633.10 | 104 | 19.587933 |

Figure 13 shows best and mean penalty values over the generations. Fined tuned GA use penalty function to handle constraints.

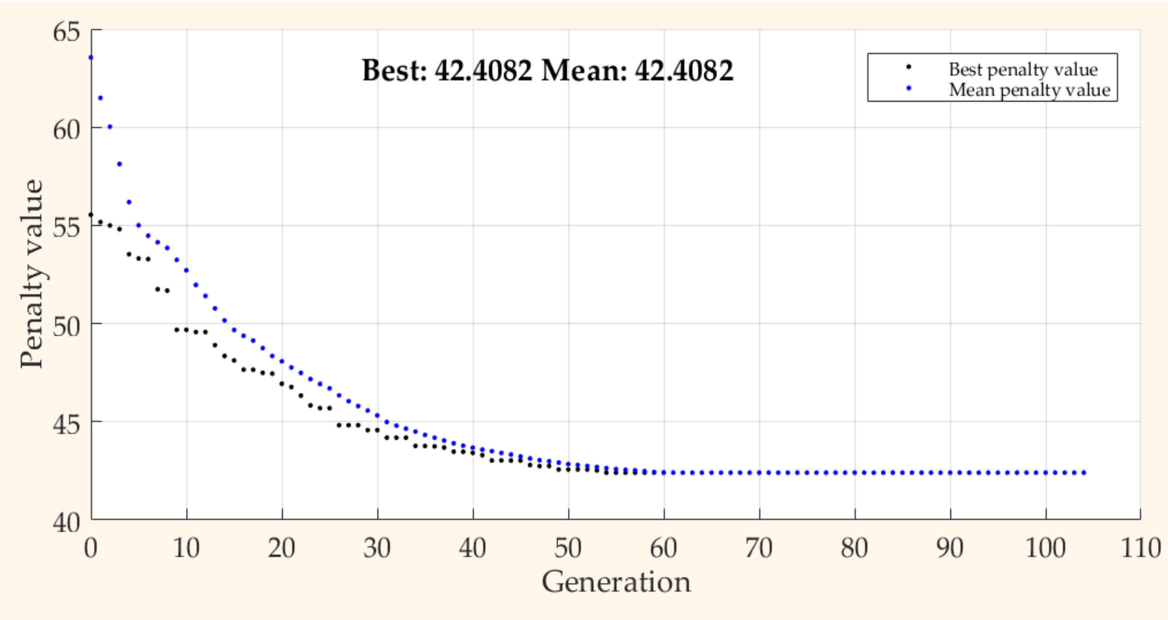


**Figure 13.** Change in penalty value with generations.

The corresponding decision variables for location selection for this case study are shown below in Tables 13–15.

**Table 13.** Construction decision of power plants.

| Location | Plant Type 1 (500 MW) (1 MW = 1000 KW) | Plant Type 2 (700 MW) (1 MW = 10,000 KW) |
|---|---|---|
| Peshawar | 0 | 1 |
| Mardan | 1 | 0 |

**Table 14.** Construction of main grids.

| | Main Grid Type 1 | Main Grid Type 2 | Main Grid Type 3 |
|---|---|---|---|
| Dir | 1 | 0 | 0 |
| Kamra | 0 | 1 | 0 |
| Haripur | 0 | 0 | 1 |

**Table 15.** Construction of local grids.

| | Local Grid Type 1 | Local Grid Type 2 | Local Grid Type 3 | Local Grid Type 4 | Local Grid Type 5 |
|---|---|---|---|---|---|
| Basham | 0 | 0 | 0 | 1 | 0 |
| Vari-Dir Bala | 1 | 0 | 0 | 0 | 0 |
| Hathian | 0 | 0 | 1 | 0 | 0 |
| Swabi | 0 | 0 | 0 | 0 | 1 |
| Nathiagli | 0 | 1 | 0 | 0 | 0 |

The problem includes 1573 decision variables and it is hard to represent all binary variables in the form of tables. However, for simplicity and visualization, Figure 14 shows the connections of the facilities planned to be constructed at different locations. To validate the results of the case study, the same problem is solved again with the help of different methodologies such as GA, FT-GA, and interior point. Table 16 shows the values of different performance measures for different algorithms.

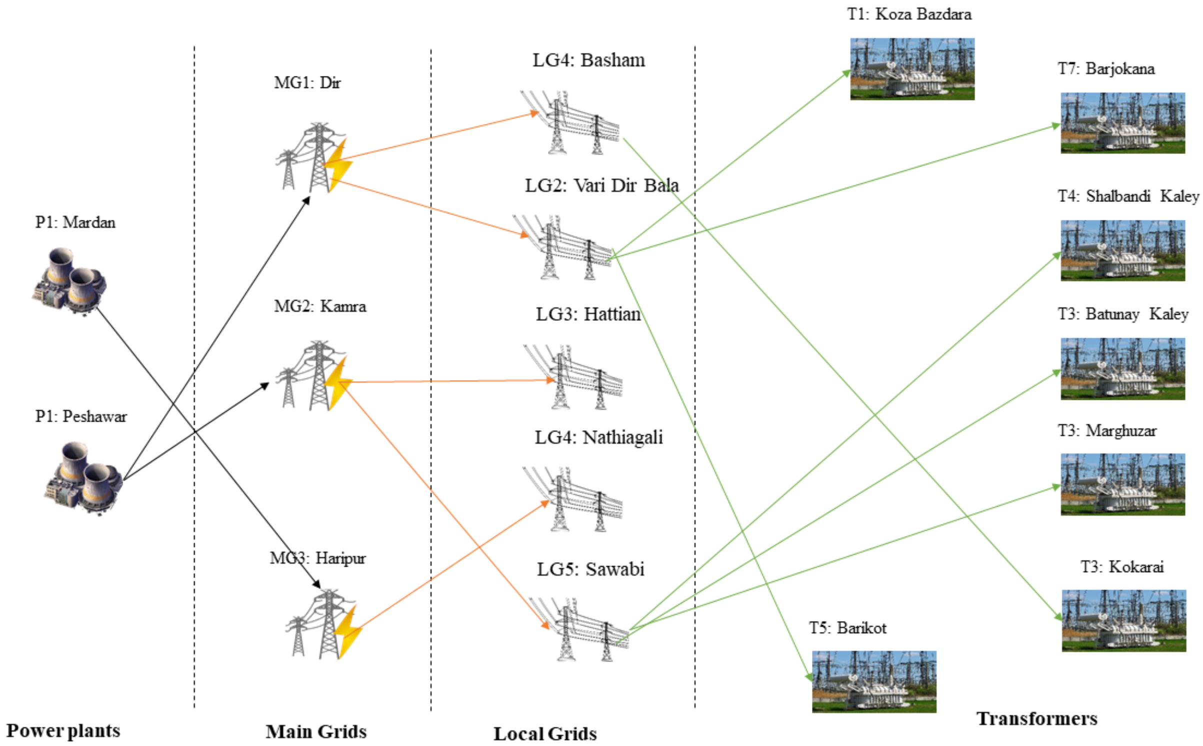


**Figure 14.** Optimized Electricity network.

**Table 16.** Comparison of different solution methodologies.

| Algorithm | Fitness Function Value | Generations | CPU Time |
|---|---|---|---|
| Genetic Algorithm | 2650.10 | 152 | 23.40217 |
| Interior point | 2762.00 | 547 | 5.786 |
| Fine-tuned GA | 2633.10 | 104 | 19.587933 |

To validate the performance of the proposed FT-GA, gap analysis, as discussed in the previous section, was performed and it was found that FT-GA performs exceptionally as compared to the other algorithms in terms of objective function value, generations, and computational time. Table 17 shows the percentage relative gap of different algorithms.

**Table 17.** Comparison of different solution methodologies.

| Algorithm | Fitness Function Value | Generations | CPU Time | Total |
|---|---|---|---|---|
| Genetic Algorithm | 0.01 | 0.46 | 3.04 | 3.51 |
| Interior point | 0.05 | 4.26 | 0.00 | 4.31 |
| Fine-tuned GA | 0.00 | 0.00 | 2.39 | 2.39 |

### *6.2. Managerial Insights*

The usefulness of research depends on its managerial application. The managers in power generation companies can make decisions about the selection of:

- Power plants at the right location.
- Main and local grids and transformers at the right location.
- This research enables managers to design transmission lines that involve minimum energy losses over distances.
- The optimization model tracks the possibilities for the transmission among power plants, main grids, and local grids. In addition to energy losses, managers can also

develop maintenance plans for the transmission lines, power plants, main grids, local grids, and transformers.

## 7. Conclusions

The main objective of the study was to design an electricity network that minimizes the total cost. The total cost included the maintenance cost of the power plant, main grids, local grid, and transformers. The cost of energy loss was kept uncertain due to the long-distances and connectivities of different nodes of the network between their starting and ending nodes, that is, power plants, main grids, local grids, and transformers. A significant contribution of the paper is the consideration of the uncertain cost of energy loss. In the first phase, a mixed-integer linear programming model was developed in which the main objective was related to the cost. Since the energy loss cost was uncertain, it was treated as a fuzzy variable. The second phase of this research included the development of a solution methodology. To solve this problem, FT-GA was proposed. To fine-tune GA, the concept of the Taguchi Orthogonal array was used which improves the performance of GA and was considered along with the Taguchi array L27. In the fourth phase, a numerical example of transmission lines was presented. A case study was solved using FT-GA. In addition to the uncertainty in energy loss, the methodological contribution is the use of FT-GA to solve the numerical example. Finally, the proposed methodology was evaluated by solving the same problem with the help of other methods such as interior-point and GA. To validate the exceptional performance of FT-GA, a gap analysis was conducted. A relative gap analysis proved that FT-GA is much better than other methods such as interior-point and GA in terms of the number of generations, faintness function value, and computational time. The future recommendations and directions include evaluating a hybrid electricity production system and installation at a different location to fulfill the electricity demand.

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