CHAPTER 4

ASSESSMENT OF SOCIO-ECONOMIC IMPACTS OF RURAL ROAD CONSTRUCTION

4.1 Introduction

The assessment performed in chapter 3 provides necessary knowledge on the criteria/sub-criteria which can be employed to assess the impacts of construction of PMGSY roads. Thus, stimulating an acute need to identify the scope and extent of these essential criteria/sub-criteria, so that comprehensive view about the impacts is achieved. Chapter 4 attempts to assess the scope of the impacted criteria/sub-criteria using computational intelligence and fuzzy MCDM approaches.

One of the key elements for rural development is the connectivity using proper roads, which enhances the passage for economic and social utilities with overall socio-economic development. An improved transport infrastructure often provides access to market and public services (health, education) for rural residents. Development of rural road infrastructure in case of developing countries can have a significant impact on the target population; it brings out economic growth with poverty alleviation (Banister and Berechman, 2003; Khandker et al., 2009). In developing countries like India, there is an emphasis on improving rural road infrastructure by taking the initiatives to connect rural habitations for better accessibility under Pradhan Mantri Gram Sadak Yojana (PMGSY). Transport infrastructure is a primary means of economic development which pave access to the markets for the agricultural produce of the rural community (Asomani-Boateng et al., 2015; Aggarwal, 2018).

It has been observed that the change in the socio-economic status of rural habitation is dependent on the circumstances or conditions of travel and access (Kanuganti et al., 2016). Tunde and Adeniyi (2012) have shown that improvement in the road quality decreases the transportation cost of agricultural products; thereby increasing the profit and income of the farmers, which further increases the production of agricultural produces. Traditionally, transportation projects are justified based on economic efficiency and are evaluated by considering a cost-benefit analysis. Most of the attempts are focused towards economic consideration; only a few are efficiently designed to assess social and economic impacts attributed by rural roads separately (Grootaert and Calvo, 2002; Aderamo and Magaji, 2010). Nirban et al. (2003) indicated the necessity of identifying the variables which can quantify (direct and indirect) socio-economic benefits incurred by the rural households. Khandker and Koolwal (2011) performed a study to distinguish the long-term and short-term effects of rural road infrastructure. The authors evaluated the change in financial gains of the most socio-economically backward class of the population.

As improved rural roads impart both social and economic benefits to the target population, there is a need to quantify socio-economic impacts in a comprehensive manner, which can demonstrate how the availability of all-weather rural road infrastructure promotes both direct and indirect benefits to the society. For effective assessment, it is necessary to have a proper understanding of socio-economic impacts (SEI) derived from the developed road infrastructure. Socio-economic impact assessment involves both qualitative and quantitative methods of assessment. Quantitative methods such as randomization, reflexive comparisons, matching, double differences, etc. are employed to assess the socio-economic impacts incurred conventionally. Randomization method is the most robust among impact evaluation methodologies. Quantitative methods, viz., reflexive comparisons, matching, double differences, etc. can deliver better understanding about SEI, provided appropriate data set is available, these are cost effective and less time consuming, and can be performed after the construction of road infrastructure (Baker, 2000). In case of cost-benefit analysis, attempts are made to assess the benefits incurred in terms of monetary returns.

Quantitative methods mentioned above for socio-economic impact evaluations reach generalized conclusions; they require specialized skills and expertise. In comparison to quantitative techniques, qualitative methods provide profound insight into the incurred impacts. Qualitative analyses are more perceptible and are based on the outcome of different surveys such as focus group (community) surveys, household surveys, which involves decision makers associated at different levels as the target population. This kind of group decision making are accomplished using various techniques, such as Delphi method (Dalkey and Helmer, 1963). It incorporates the judgments provided by the group of participants involved in the decision-making process by means of questionnaires. Moreover, when traditional Delphi approach is integrated with the fuzzy set theory, it overcomes the inconsistency and risks associated with the conventional method and helps in reducing the time and cost associated with overall questionnaire survey process (Hsu et al., 2010). It also assists in the group decision-making process in a comprehensive manner by overcoming the fuzziness associated with the opinions of decision makers (Singh and Vidyarthi, 2008; Kanuganti et al., 2016).

Although, different quantitative and qualitative methods are used for assessing socio-economic impacts, the main problem is the modeling of human perceptions under given circumstances as well as some of the techniques mentioned above (i.e., Randomization, matching, cost-benefit analysis, etc.) are cost-intensive and time-consuming. They lack in integrating the uncertainties that may arise in the data set which are dependent on the viewpoints of the target population, leading to considerable bias assessment. For this reason, researchers are being encouraged to employ comprehensive methods for assessing the impacts incurred. In recent times researchers are focused on adopting innovative techniques and methodologies to assess various issues associated with transportation studies (road infrastructure, traffic studies, etc.). Among the new techniques, Computational Intelligence (CI) approaches offer factual advantages and are becoming popular, as it can handle complexity associated with the information to be acquired from the data set collected specially to enhance the effectiveness and environmental coherence of transportation system. As each of these techniques is proven as effective, they can be explored to employ in the transportation field in a symbiotic manner (Akbulut et al., 2004). Adaptive Neuro-Fuzzy Inference System (ANFIS) is one such technique. It is developed by integrating the concepts of neural networks and fuzzy logic. ANFIS technique captures the benefits of both neural networks and fuzzy logic and allows in strategic decision making with high-level proficiency in a systematic manner. It is widely used in condition identification (Hosseinlou and Sohrabi, 2009), decision making (Pamučar et al., 2013), prediction modeling (Lee et al., 2015), and many other fields. It provides results with a tolerance of ambiguity, uncertainty, approximation and handle complex social and human systems comprehensively by utilizing linguistic information in the form of human perception and measured data (Islam et al., 2016), as well as it is time and cost effective. Thus, it is well understood that the ANFIS technique can overcome the research shortcomings available in the existing techniques employed to assess socio-economic impacts. It can be a significant value addition to the literature available on SEI due to development of road infrastructure.

Therefore, in the present study an attempt has been made to develop a holistic methodology to assess the socio-economic impacts (SEI) incurred by the target population due to construction of rural roads by employing ANFIS and fuzzy Delphi method. It considers their prolific nature and efficiency of evaluation. Furthermore, it also presents a comparison of the evaluation capabilities of ANFIS and fuzzy Delphi techniques. The key objective of this research is two-fold: (a) to assess and highlight how the construction of rural (PMGSY) roads impacts the socio-economic status of rural habitations by employing computational intelligence and soft computing approach, and (b) to explore and exploit the evaluation capabilities of above mention approaches by developing novel methdology, thereby paving a way to the decision and policy makers to implement essential policies. The effectiveness of methodology is presented by employing a case study for 27 habitations connected through rural (PMGSY) roads constructed in the year 2013-14 in Jhunjhunu district of Rajasthan state, India. A total of five main criteria and 33 sub-criteria are considered for socio-economic impact assessment (SEIA) model to demonstrate the cause-effect relationships. The methodology presented herein is capable of efficiently dealing with the complexities that may result from group decision-making process.

4.2 Methodology

The present study proposes a methodology by employing a case study approach for selected habitations of Jhunjhunu district of Rajasthan state, India, to evaluate socio-economic impacts on rural habitations/communities due to the deliverance of rural road infrastructure. The current study is based on ex-post research design (i.e., after the construction of roads), as the objective is to identify the actual impacts of roads after their construction, and to draw the valuable insights from the assessment that how much the change has occurred. The approach focuses on identifying and measuring the net impacts occurred based on the perception of impacted population and statistical control comparison (Braathen and Hervik, 1997). The ex-post evaluation approach mainly focuses on two aspects: (i) impact – which is expected in certain period of time after the construction of roads, and (ii) sustainability – whether the impacts are continuously produced after the implementation of the project. The ex-post approach helps in investigating the effectiveness of implementation of construction of roads by evaluating improvement effects in the social and economic conditions of rural households (Louwa et al., 2013). The ex-post approach also helps to verify the assumptions which are made earlier while evaluating impacts in certain period of time after the construction of roads.

Thus, present study focuses on assessing and measuring the impacts based on ex-post approach by considering the perception of rural households. This is important especially when no control group are available for statistical comparison. Therefore, from assessment design point of view, only those habitations are identified where the roads are intended to improve the socio-economic condition of rural inhabitants. In the current research, ANFIS using the subtractive algorithm as well as fuzzy Delphi method (FDM) are employed to assess the socio-economic impacts incurred by the construction of rural roads. Furthermore, the results of ANFIS is compared with the results obtained from FDM, to assess their computational capabilities.

4.2.1 Study area

A case study is taken for the habitations connected through PMGSY roads in 6 (out of 8) blocks of Jhunjhunu district, Rajasthan, India. Total 27 roads are considered along the selected habitations as shown in Fig. 4.1. The sampling of these roads defining the study area is adjusted based on factors such as the year of their construction (i.e., PMGSY roads constructed in 2013-14 are selected) as most socio-economic changes take time to occur. The roads are also selected based on the population of habitations as well as geographical location. The population of these habitations' ranges from 350 to 390 as per 2011 census. The habitations selected belong to the arid region of the state, which has extreme climatic conditions with very hot summers and very cold winters followed by poor rainfall. Map of blocks of Jhunjhunu district representing through routes and habitations location considered for study are shown below in Fig. 4.1. Table 4.1 shows different blocks and habitations of Jhunjhunu district, Rajasthan state, India used in the case study.

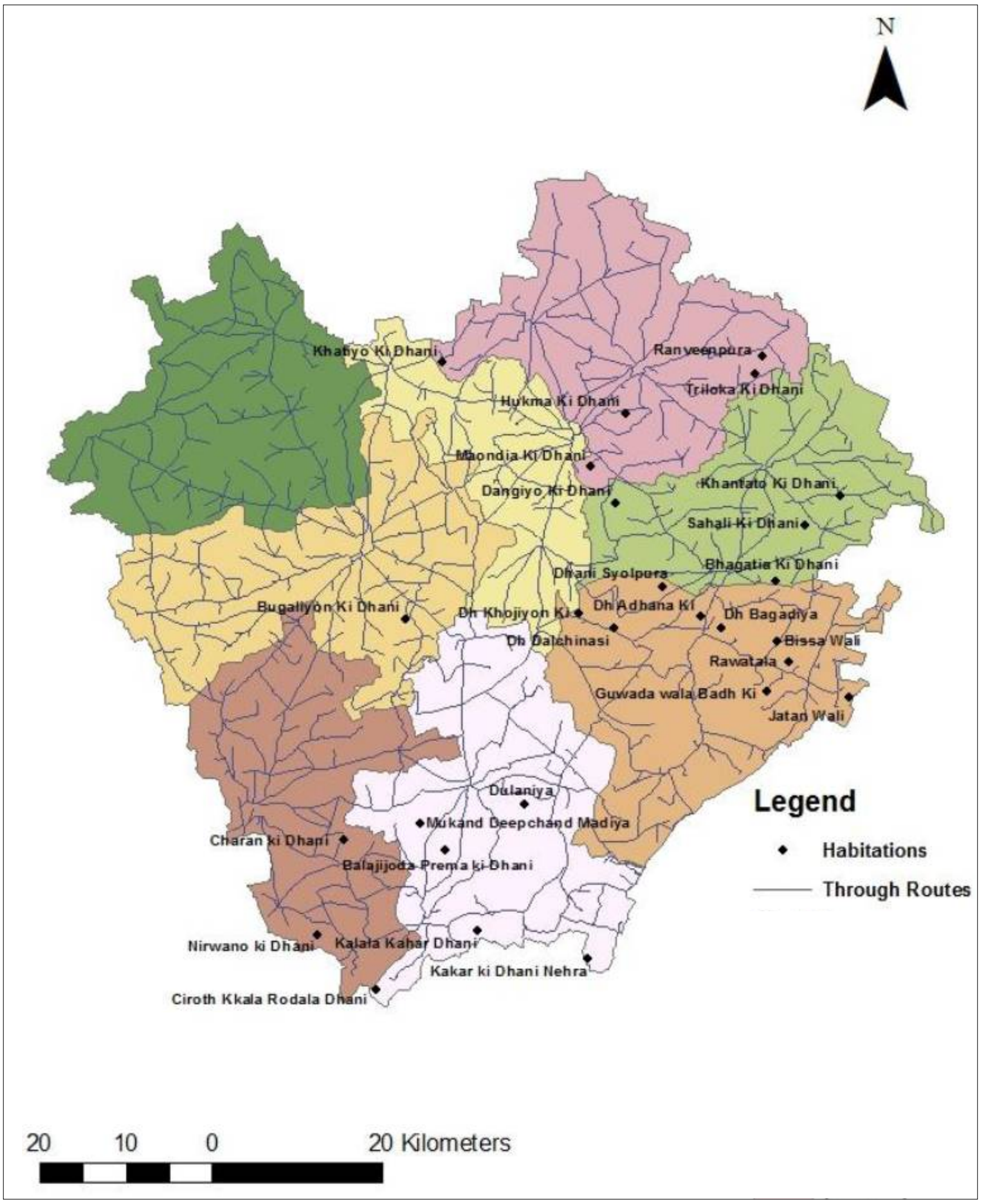


Fig. 4.1 Map of blocks of Jhunjhunu district with through routes and habitations location

Table 4.1 Blocks and habitations of Jhunjhunu district, Rajasthan, India (study area)

Block	Habitation	Population
Buhana	Bhagatia Ki Dhani	350
	Dangiyo Ki Dhani	390
	Sahali Ki Dhani	390
	Khantato Ki Dhani	360

Jhunjhunu	Bugaliyon Ki Dhani	375
	Jatan Wali Dhani	350
	Dhani Syolpura	350
	Dhani Dalchinasi	350
	Dhani Khojiyon Ki	350
Khetri	Bissa Wali Dhani	350
	Dhani Adhana Ki	350
	Dhani Bagadiya	350
	Guwada wala Badh Ki	350
	Rawatala	350
	Ranveenpura	350
	Triloka Ki Dhani	360
Surajgarh	Maondia Ki Dhani	350
	Khatiyo Ki Dhani	350
	Hukma Ki Dhani	350
	Nirwano ki Dhani	370
Nawalgarh	Charan ki Dhani	350
	Kalala Kahar Dhani	350
	Ciroth Kkala Rodala Dhani	350
Udaipurwati	Kakar ki Dhani Nehra	350
	Dulaniya	360
	Balajijoda Prema ki Dhani	375
	Mukand Deepchand Madiya	360

4.2.2 Selection of SEIA criteria/sub-criteria

Considering the analysis presented in Chapter 3 of the thesis, total 33 socio-economic sub-criteria under five main criteria are used to assess social and economic phenomenon of a community. These criteria/sub-criteria provide insights into the likely impacts of delivered infrastructure on the target community and help in monitoring the rural development. Therefore, based on the analysis performed and presented in Chapter 3, 33 sub-criteria under five main criteria, viz., transport facility, income status, health facility, education facility and quality of the neighborhood considered for assessing their scope and extent is enlisted below in Table 4.2.

Table 4.2 Socio-economic impact assessment criteria and sub-criteria with symbols

Criteria	Sub-criteria	Symbol
	Travel time using public transportation	T_{TTPUB}
	Travel time using private transportation	T_{TTPVT}
	Public transportation units	T_{PUBTU}
Transport facility	Private transportation units	T_{PVTTU}
	Frequency of Public transportation	T_{PUBF}
	Public transportation cost	T_{PUBTC}
	Private transportation cost	T_{PVTTC}
	Individual Income	I_{II}
	Household income	I_{HH}
	Income of self-employed from agriculture	I_{SA}
Income status	Income of wage labor from agriculture	I_{WA}
	Income from Livestock	I_{L}
	Income of unskilled labor from agriculture	I_{UA}
	Income of unskilled labor from non-agriculture	I_{UNA}
	Use of health facility	H_{FU}
	Availability of health clinic	H_{CA}
	Availability of primary health center	H_{PHCA}
Health facility	Access to the mode of transport for health facility	H_{HAM}
	Travel time to reach a health facility	H_{TT}
	Health Status (anthropometric measures up to adolescent age)	H_{HSANT}
	Literacy rate of male	E_{MLR}
	Literacy rate of female	E_{FLR}
	Percent of male children attending schools	E_{MAS}
Education Facility	Percent of female children attending schools	E_{FAS}

	Access to the mode of transport for Education facility	E_{AM}
	Travel time to reach education facility	E_{TT}
	Availability of Preschools	E_{PRESA}
	Availability of Primary schools	E_{PRISA}
	Ownership of personal phone	Q_{PPO}
Quality of	Ownership of Television	Q_{TVO}
Neighborhood	Livability	Q_{L}
	Involvement in Social-gathering within the village	Q_{SGIV}
	Involvement in Social-gathering outside the village	Q_{SGOV}

It is to be noted that the indicators such as "income from livestock" or "ownership of television" or "ownership of personal phone" relate to the improvements in income and quality of life of rural inhabitants after the construction of roads, as these habitations have been at remote places and had low accessibility to new avenues of income and personal recreation possessions. It has been observed that if roads are provided, villagers have better accessibility and hence they may have better employment. Thus, their living standards are improved, which can be assessed directly or indirectly by correlating even by income from livestock or ownership of television or ownership of personal phone. All these variables become even more important in case of developing worlds.

4.3 Methods and material

4.3.1 Adaptive Neuro-fuzzy Inference System (ANFIS)

Artificial Intelligence (AI) approach is broadly categorized into two sections, one which concentrates on the development of the knowledge-based system (KBS) and the other is computational intelligence. Among computational intelligence techniques, neural networks have an intrinsic tendency in storing the acquired pragmatic information which can be used by the researchers in various real-life applications (Wagale et al., 2016). These techniques can simulate the output results in a robust manner using the concepts of biological nervous system and can reproduce numerical paradigms. However, recently a hybrid methodology of neural networks called Adaptive Neuro-fuzzy Inference System (ANFIS) is becoming popular due to its ability to address very complex problems. This technique is the integration of neural network learning algorithms along with fuzzy based inference system. Application of ANFIS is well implemented successfully in numerous areas of transportation studies, viz., travel behaviour and mode choice modelling, estimation of que lengths at signalized intersections, road accident and traffic flow prediction modelling (Pribyl and Goulias, 2003; Andrade et al., 2006; Tortum et al., 2009; Mucsi et al., 2011; Lee et al., 2015). ANFIS can be employed to quantify real-life situations by incorporating substantial human perceptions using appropriate data sets and their interrelationships. When it is combined with subtractive clustering it becomes one of the most innovative techniques of artificial intelligence in comparison with techniques like support vector machines (SVM), logistic regression, in terms of prediction performance. It can reach up to 94% accuracy and has intrinsic advantage over other techniques because it inherits characteristics such as parallel computing, adaptive learning etc. (You et al., 2017).

The hybrid approach can be applied for constructing complex and nonlinear relationships among a given set of data points (input and output data set). As ANFIS approach is the integration of fuzzy inference system (FIS) and artificial neural networks (ANN), it takes into account the operations of both FIS and ANN (Jang, 1993). Thus, in ANFIS modelling, a strategic system is developed which combines significant aspects of both FIS and ANN respectively. Many researchers have developed fuzzy inference methodologies by deriving IF-THEN rules that are widely used in assessing different problems under the uncertain environment (Mamdani and Assilian, 1975; Takagi and Sugeno, 1985). Takagi and Sugeno's FIS model are expressed in the form of a constant coefficient or a linear equation with "zero order" or "first-order" Sugeno models respectively. Logically ANFIS employs Sugeno fuzzy inference system to develop fuzzy rules with a given dataset. Fuzzy rules (IF/THEN) in ANFIS for first-order Sugeno fuzzy inference system consisting of two inputs (X) and (Y) with single output (f) can be expressed as:

Rule 1: IF X is A_1 and Y is B_1, THEN $f_1= l_1X+m_1Y+n_1$

Rule 2: IF X is A_2 and Y is B_2, THEN $f_2= l_2X+m_2Y+n_2$

where A_1, A_2, B_1, and B_2 are linguistic labels and l_1, l_2, m_1, m_2, n_1, and n_2 are linear parameters.

The ANFIS architecture consists of five-layers as shown in Fig. 4.2. The layers are connected with direct links and nodes representing different shapes and utilities. The circular nodes in the architecture depict fixed type nodes, whereas square nodes represent adaptive nodes. The layer-wise process followed in ANFIS is elucidated as below:

Layer 1 (Fuzzification): This layer develops membership functions by the fuzzy sets; input attributes are introduced in this layer. Every node of this layer is an adaptive node. The input and the output functions along with their membership relation are expressed in equation (4.1) and equation (4.2) as given below:

$o_i^1 = \mu_{Ai}(X)$; i = 1, 2. (4.1)

$o_j^1 = \mu_{Bj}(Y)$; i = 1, 2. (4.2)

where X and Y are the inputs in layer 1 to the adaptive nodes A_i and B_j respectively, which represent linguistic terms of input criteria, $\mu_{Ai}(X)$ and $\mu_{Bj}(Y)$ are the membership functions of linguistic terms A_i and B_j respectively.

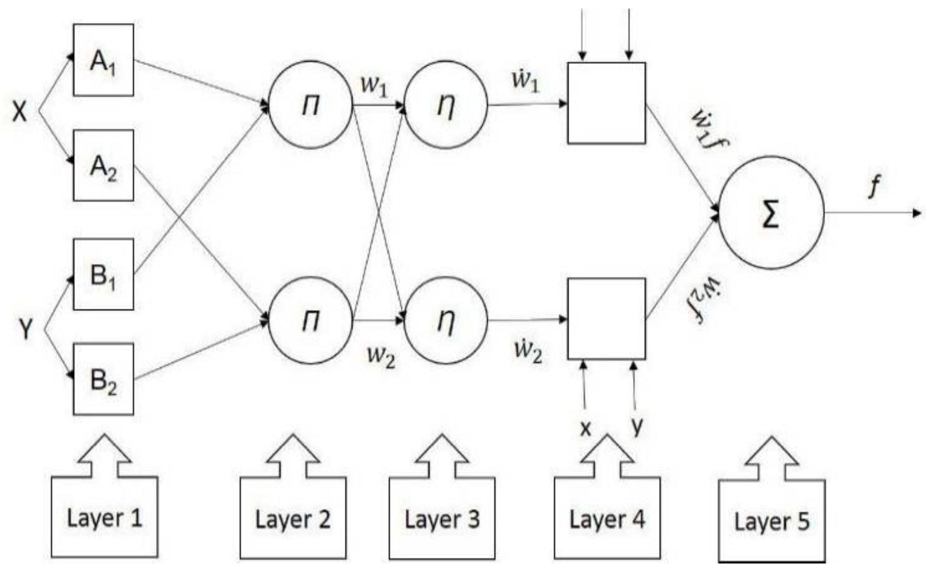


Fig. 4.2 The generalized model architecture of ANFIS

Layer 2 (Fuzzy AND): The layer produces the output which depends upon the fuzzy input of the preceding layer by activating necessary fuzzy rules. It is labelled as (Π) and performs product operation. The output of this layer (o_i^2) (firing strength) is the degree to which the developed rule matches the given inputs and is given in equation (4.3) as mentioned below:

$$o_i^2 = w_i = \mu_{Ai}(X)\mu_{Bi}(Y); \text{ i = 1, 2.} \tag{4.3}$$

where w_i is the firing strength.

Layer 3 (Normalization): This layer performs normalization of the fuzzy rule extent and is represented as (η). The output of this layer (o_i^3) are normalized and is expressed in equation (4.4) as given below:

$$o_i^3 = \dot{w}_i = \frac{w_i}{\sum w_i}; \text{ i = 1, 2.} \tag{4.4}$$

where $\dot{w}_i$ is the ratio of firing strength to the summation firing strengths.

Layer 4 (Defuzzification): The fourth layer of the architecture evaluates the inputs provided by each fuzzy rule contributing to the output. In this layer, the nodes are known as adaptive nodes. The output of this layer (o_i^4) is the product of normalized outputs of the previous layer and are of first order polynomial. The output of this layer is given in equation (4.5) as mentioned below:

$$o_i^4 = \dot{w}_i f = \dot{w}_i\,(l_i X + m_i Y + n_i)\text{ ; i = 1, 2.} \tag{4.5}$$

where f is the output of the i^{th} rule.

Layer 5 (Output layer): Finally, the fifth layer gives overall output by considering all the inputs from the previous layers. This layer consists of a single fixed node (Σ) which performs the summation of all the inputs coming from previous layers to give overall output (o_i^5) of the model and is expressed in equation (4.6) as mentioned below:

$$o_i^5 = \sum_{i=1}^{2} \dot{w}_i f; \text{ i = 1, 2} \tag{4.6}$$

where f is the output of the i^{th} rule.

4.3.2 Subtractive clustering algorithm

The most important step in the ANFIS model is the determination of an optimum number of fuzzy rules required to obtain the desired output. For instance, if there are six input values with three membership grades, the number of rules will be ($3^6 = 729$) which is quite large for any learning techniques to comprehend. It may increase further with an increase in input variables, thus leading to the problem of “curse of dimensionality”. To overcome this problem of “curse of dimensionality” associated with ANFIS operation; subtractive clustering approach can be useful which is based on the concentration of data points and their closeness with the actual values. The main steps of the algorithm can be briefed as follows. First, it chooses the data point among the data set having maximum aptitude as the first cluster centre. Next, it eliminates all the data points neighbouring the first cluster with consideration to a range of influence (usually 0.5), and lastly, it performs iteration process such that every data point are contained within the radii of the cluster axis (considered to be 1.25). Table 4.3 represents the sample parameters considered for the subtractive clustering algorithm, which are taken based on literature available on ANFIS using subtractive clustering algorithm (Relich and Pawlewski, 2016).

Table 4.3 Subtractive clustering parameters

S. No.	Name	Value
1	Range of influence	0.3
2	Squash factor	1.25
3	Accept ratio	0.5
4	Reject ratio	0.15

4.3.3 Fuzzy Delphi

Edelman (1985) proposed the concept of fuzzy set theory along with its integration to the traditional Delphi method to overcome the vagueness and uncertainty associated with the group decision-making process. Kaufmann and Gupta (1988) have also presented an application of fuzzy Delphi method in a group decision-making process. Chang and Wei (2000) concluded that fuzzy Delphi method provides an opportunity to overcome the uncertainty (fuzziness) arising from the perception of decision makers in optimizing the objectives. Fuzzy Delphi method can also overcome the number of survey rounds required to attain common consensus in the group decision-making process; it also reduces expenditure and duration incurred for the execution of group decision-making process by maintaining its originality as compared to that of traditional Delphi approach (Hsu et al., 2010; Habibi et al., 2015). In the present study application of fuzzy Delphi method is performed by employing triangular fuzzy numbers to assess the perceptions of stakeholders (focus group participants). The stepwise procedure of fuzzy Delphi method is explained below.

Step: 1 Collection of perception of stakeholders (focus group participants)

A focus group survey is conducted for assessing the socio-economic impacts of PMGSY roads by considering five main criteria and 33 sub-criteria as key factors. The perceptions of stakeholders (focus groups participants) are taken as assessments scores in correspondence with each criterion. Each of the sub-criteria concerning main criteria is assessed on a scale of 5 down to 1 (i.e., 5 = highest change; 1 = lowest change). The range value of change scale is established by taking the opinion of experts working in this field and is deduced after interacting with their suggestions. Further, for ease of assessment and removal of geometrical biases associated with dimensions of the input data, and to smoothen from the influence of criteria on one another. This collected data is normalized and is set in the scale range of 0 – 1. The min-max normalization technique is used for transforming data linearly from the scale of 1 - 5 to 0 - 1, as specified in equation (4.7) (Nowroozi et al., 2009; Phogat and Singh, 2013):

$$x_{norm} = \frac{(x_i - x_{min})}{(x_{max} - x_{min})} \text{; i = 1, 2, ..., k.} \tag{4.7}$$

where x_i = i^{th} scale value of the criteria, x_{norm}= normalized scale value of criteria, x_{min} = minimum scale value of the criteria, and x_{max}= maximum scale value of criteria.

Step: 2 Setting up triangular fuzzy numbers

In the present study, the triangular fuzzy number for each of the sub-criteria is evaluated based on the categorical scores obtained from the focus groups, after the process of normalization. The reason for adopting the triangular fuzzy scale is the dynamic change in the scaled valued of perception of stakeholders. The triangular fuzzy number is the best suitable for representing when there is dynamic variation and can be deduced with simplicity in comparison with other fuzzy scales such as trapezoidal, Gaussian etc. (Liu, 2013). The study also considers the literature (Liu, 2013; Tahriri et al., 2014) available on FDM which employed triangular fuzzy scale. The triangular fuzzy scale for study adopted is represented in Fig. 4.3. Table 4.4 shows the linguistic definition of triangular fuzzy numbers.

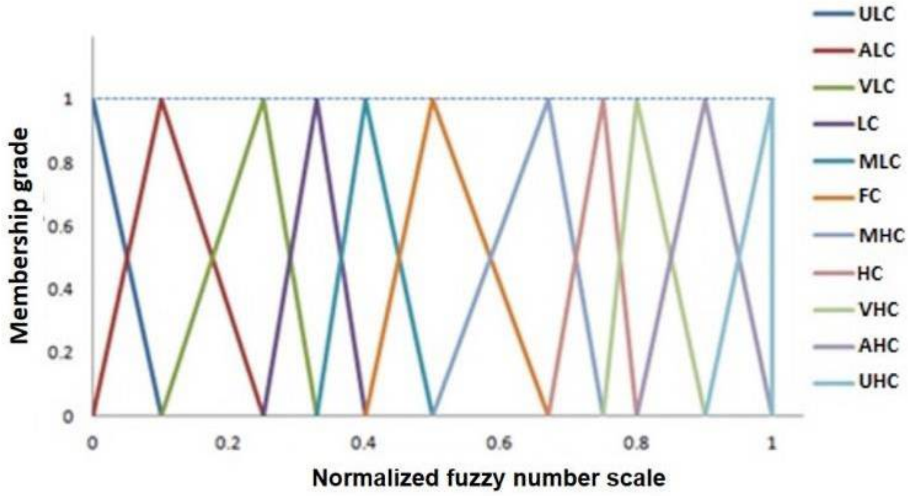


Fig. 4.3 The fuzzy number scale

Table 4.4 Definition of fuzzy numbers

Fuzzy numbers	Definition	Symbol
(0.9, 1, 1)	Ultimate high category	UHC
(0.8, 0.9, 1)	Absolutely high category	AHC
(0.75, 0.8, 0.9)	Very high category	VHC
(0.67, 0.75, 0.8)	High category	HC
(0.5, 0.67, 0.75)	Moderate high category	MHC
(0.4, 0.5, 0.67)	Fair category	FC
(0.33, 0.4, 0.5)	Moderate low category	MLC
(0.25, 0.33, 0.4)	Low category	LC
(0.1, 0.25, 0.33)	Very low category	VLC
(0, 0.1, 0.25)	Absolutely low category	ALC
(0, 0, 0.1)	Ultimate low category	ULC

Step: 3 Aggregation of perceptions

In this step, the mean fuzzy weights for each of the sub-criteria are evaluated. This can be illustrated as follows: suppose (w_t) is the categorical weight of the sub-criteria (C_1, C_2, C_3, …., C_n) given by the stakeholder S_j then the aggregation of stakeholders is formulated in equation (4.8) given below:

$$S_{ij} = \left(\frac{1}{m}\right) \otimes \left(S_{ij}^{1} \oplus S_{ij}^{2} \oplus \ldots\ldots \oplus S_{ij}^{m}\right) \tag{4.8}$$

where $\otimes$ represents multiplication of fuzzy numbers and $\oplus$ represents the addition process of fuzzy numbers, S_{ij} is the mean fuzzy evaluation of alternative i under sub-criterion j and is represented as triangular fuzzy number as given below.

$S_{ij} = (pS_{ij}, qS_{ij}, rS_{ij})$

where $pS_{ij} = \left(\frac{\sum_{ij}^{m} pS_{ij}^{k}}{m}\right), qS_{ij} = \left(\frac{\sum_{ij}^{m} qS_{ij}^{k}}{m}\right), rS_{ij} = \left(\frac{\sum_{ij}^{m} rS_{ij}^{k}}{m}\right)$. Then fuzzy weight $\widetilde{w}_t$ of the j sub criterion is $\widetilde{w}_t = (a_t, b_t, c_t)$; for t = 1, 2, …, k.

<u>Step: 4</u> Defuzzification of fuzzy weights

Finally, the synthetic fuzzy weight for each sub-criterion of a given criteria is defuzzified to establish best non-fuzzy performance score (real number) (BNS). In the present study, the center of area technique is used to perform defuzzification process. The deffuzified scores, BNS can be obtained by using equation (4.9) as shown below, Table 4.5 shows non-fuzzy performance scores.

$$BNS_{ij} = \left[\frac{(rS_{ij} - pS_{ij}) + (qS_{ij} - pS_{ij})}{3}\right] + pS_{ij} \tag{4.9}$$

Table 4.5 Non-fuzzy performance score

Fuzzy numbers	Definition
1	Ultimate high category
0.9	Absolutely high category
0.8	Very high category
0.75	High category
0.67	Moderate high category
0.5	Fair category
0.4	Moderate low category
0.33	Low category
0.25	Very low category
0.1	Absolutely low category
0	Ultimate low category

4.3.4 Determination of sample

In the present study, sample determination is conducted in reference with past studies (Asomani-Boateng et al., 2015; Wagale et al., 2019). Sample population (focus group) for data collection of the study is adjusted with the population of each habitation, as well as, according to the selected PMGSY roads. The selected sample resembles the total population of each habitation. The study employs a stratified random sampling technique. The total population served by these roads is 9640 individuals, which has been identified from the secondary sources. The number of habitations considered for the study are proportional to the number of PMGSY roads identified. Therefore, considering 95% confidence level and 5% of margin error, a sample size of n = 370 individuals is identified to have appropriate sample size of the data as defined as possible (i.e., for each of the habitation one focus group is selected. Thus, making total 27 focus groups, such that each of the focus group consists of 14 participants as shown in Table 4.6). Also, each of the focus group is identified in such a way that it involves participants belonging to a different gender (male and female), age group (i.e., 16 to 45), and livelihoods (e.g., agriculture, jobs such as peons, clerks, school teachers, students, etc.).

Table 4.6 Coverage of study area (blocks and habitations of Jhunjhunu district, Rajasthan, India)

Block	Habitation	Focus group size	Region total
	Bhagatia Ki Dhani	14	
Buhana	Dangiyo Ki Dhani	14	56
	Sahali Ki Dhani	14	
	Khantato Ki Dhani	14	
Jhunjhunu	Bugaliyon Ki Dhani	14	14
	Jatan Wali Dhani	14	
	Dhani Syolpura	14	
	Dhani Dalchinasi	14	
	Dhani Khojiyon Ki	14	
Khetri	Bissa Wali Dhani	14	126
	Dhani Adhana Ki	14	
	Dhani Bagadiya	14	

	Guwada wala Badh Ki Dhani	14	
	Rawatala	14	
	Ranveenpura	14	
	Triloka Ki Dhani	14	
Surajgarh	Maondia Ki Dhani	14	70
	Khatiyo Ki Dhani	14	
	Hukma Ki Dhani	14	
	Nirwano ki Dhani	14	
Nawalgarh	Charan ki Dhani	14	28
	Kalala Kahar Dhani	14	
	Ciroth Kkala Rodala Dhani	14	
	Kakar ki Dhani Nehra	14	
Udaipurwati	Dulaniya	14	84
	Balajijoda Prema ki Dhani	14	
	Mukand Deepchand Madiya	14	

4.3.5 Acquisition of data

The study employs a case study for habitations belonging to 6 (out of 8) different blocks of Jhunjhunu district of Rajasthan, India. It is mainly because PMGSY roads were constructed only in these 6 blocks during the study work of this research. Data about various indicators which define SEIA is collected through focus group survey from the identified habitations, connected by rural (PMGSY) roads. The focus group survey is conducted during (April and May 2016). To have the knowledge and to overcome the risks associated with data collection, preliminary discussions with rural inhabitants of the selected habitations are also conducted. Focus group surveys are facilitated by using a questionnaire, designed to collect data of both qualitative and quantitative nature; it also considers the inputs from preliminary discussions conducted before the final focus group discussion. It consists of five sections; each section represents criteria, which influence the socio-economic development of the rural inhabitants.

The information for the focus group survey is formulated with closed-ended questions to gauge necessary information in terms of categorical manner as shown in Table 4.7. To avoid any error in the data received from a focus group survey, further feedbacks are taken at the end of every section of the questionnaire to crosscheck them.

Table 4.7 Questionnaire information

Questionnaire category	Target respondents	Criteria	Information provided section wise
Community level	Participants belonging to a different gender (male and female), age group (i.e., 16 to 45), and livelihoods (e.g., agriculture, jobs such as peons, clerks, school teachers, students, etc.), from the habitation.	Transport facility	Travel and trip characteristics, the reliability of the transport facility, passenger and freight charges
		Income status	Change in income pattern, occupation, and availability of any other income source to the participants as the impact of new roads
		Health facility	Impact of roads on quality and availability of health services
		Education facility	Impact of roads on the availability of education facility, school enrolment, attendance and access
		Quality of neighbourhood	Changes in quality and life of neighborhood, expenditure, and ownership of material property, as well as a change in conditions of social inclusion within and outside the community of the participants

All required data of Table 4.7 have been collected through focus group survey using the questionnaire given in Appendix I. On similar lines, data with respect to other habitations are collected.

4.4 Model assessment

4.4.1 Model Development (Training) for ANFIS

The present study out-of-sample prediction technique is employed to assess the capability of the model. Accordingly, as mentioned earlier, the data set for each criterion is divided into two subsets with 70% of data set for training and 30% for testing. Five models are developed for each of the criteria (viz., transport facility, income status, health facility, education facility and quality of neighbourhood) separately and trained for the data set with the application of ANFIS tool of MATLAB 2016. To assess the performance of the developed model trial and error method is employed. The important parameters defining the ANFIS model for quality of neighbourhood model are listed below in Table 4.8. Fuzzy rules for the quality of the neighborhood model are shown in Fig. 4.4. Membership functions of the sub-criteria "involvement in social-gathering outside the village" (Q_{SGOV}) of quality of neighbourhood criteria are depicted as below in Fig. 4.5. The parameters employed for ANFIS models are obtained from the literature (Islam et al., 2016; Keshavarzi et al., 2017).

Table 4.8 Parameters defining the ANFIS model for quality of neighborhood criteria

ANFIS Parameters	
Number of input criteria	5
Number of layers	5
Training algorithm	Back propagation
Number of fuzzy rules	12
Hidden layer transfer function	Tan-sigmoid
Sealing method	Normalization
Output layer transfer function	Linear
Epochs	10
Error tolerance	0.0
Membership function	Gaussian
FIS generated using	Subtractive clustering

Considering the back propagation training algorithm, Tan-sigmoid transfer function has been used. The transfer function helps in implementation of back propagation training algorithm in smooth and continuous manner and helps in mapping the data with significant accuracy. The output surface for the quality of the neighborhood model (QNA) is shown in Fig. 4.6. It is also inferred from Fig. 4.6, that as the input values with respect to ownership of personal phones (Q_{PPO}) and ownership of television (Q_{TVO}) sub-criterion are increased, the output value of quality of neighbourhood model (QNA) also increases.

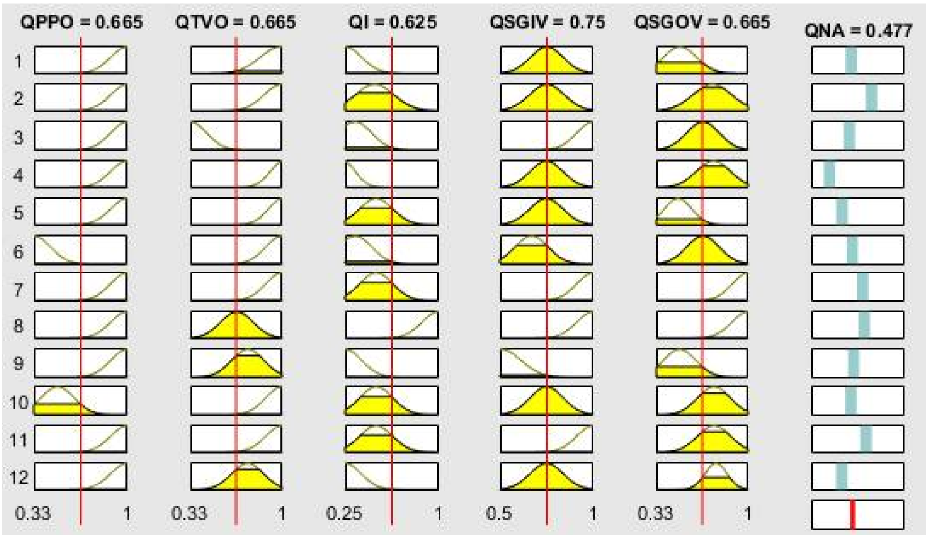


Fig. 4.4 Rule view of ANFIS for training data of quality of neighborhood criteria

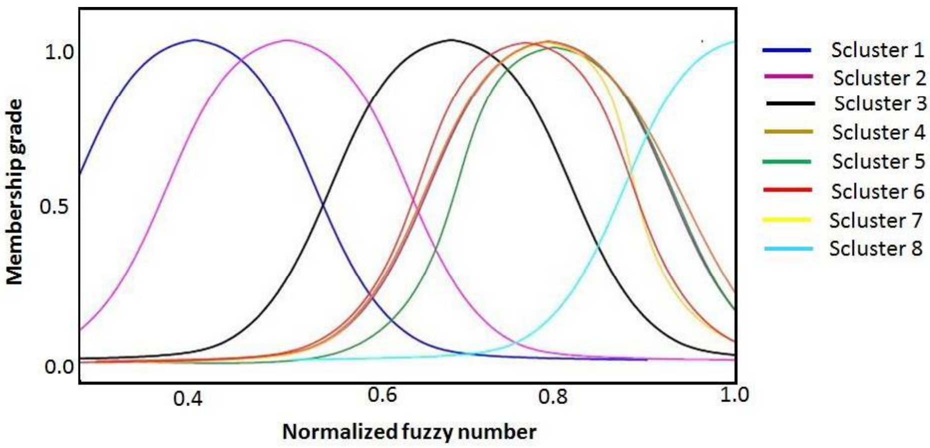


Fig. 4.5 Membership functions of the sub-criteria “involvement in social-gathering outside the village”

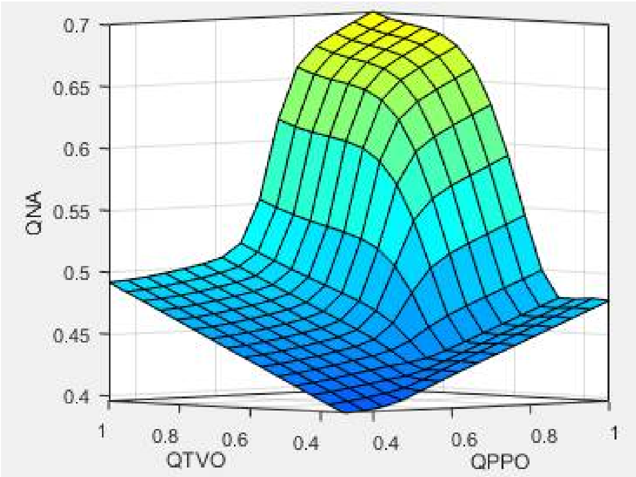


Fig. 4.6 Output surface for quality of neighborhood criteria

4.4.2 Model evaluation criteria

In the current study, the performance of the models is evaluated by considering of two statistical criteria, viz., the correlation coefficient (R) and the root-mean-square error (RMSE), which can be expressed by equations (4.9) and (4.10) as mentioned below:

$$R = \frac{\sum_{i=1}^{N}(t_i - t_{avg}) \times (p_i - p_{avg})}{\sqrt{\sum_{i=1}^{N}(t_i - t_{avg})^2} \times \sqrt{\sum_{i=1}^{N}(p_i - p_{avg})^2}} \tag{4.9}$$

where t_i = i^{th} target class, t_{avg} = mean of target class, p_i = i^{th} predicted class, and p_{avg} = mean of predicted class.

$$\text{Root mean square error} = \sqrt{\frac{\sum_{i=1}^{N}(t_i - t_{avg})^2}{N}} \tag{4.10}$$

where N is the total number of data observations.

4.5 Results and discussions

In the present study, five different models are developed with respect to each of the criteria (viz., transport facility, income status, health facility, education facility and quality of neighbourhood) using ANFIS and FDM. To assess the socio-economic impacts incurred due to the construction of rural roads, a case study of PMGSY roads is employed. For ANFIS modeling, the data set is divided into two sections, viz., training data and testing data. The developed models are assessed on the basis of two evaluation criteria, viz., the correlation coefficient (R) and the root mean square error (RMSE). Fig. 4.7 illustrates the performance of the models for both testing and training data for ANFIS. The R-value for income status criteria model has been found high in both training and testing with the values of 0.7368 and 0.8621 respectively. The RMSE values have been found as 0.1152 and 0.1715 respectively, which are relatively low. Thus, the model performs better, as the value of R ranges between -1 to 1 and RMSE ranges between 0 and 1, higher the R with lower RMSE value is a good fit. Moreover, the model for quality of neighbourhood criteria shows a similar pattern for R and RMSE values of 0.9205 and 0.2617 respectively for training, whereas in testing, these values are taken as 0.8389 and 0.1209 respectively.

From the analysis, it is observed that the models dealing with income status and quality of neighbourhood perform satisfactory as compared to the other models developed. The model for education facility shows low R values during both in training and testing phases, whereas the RMSE value for training model of education facility is high as compared to the RMSE values of all other models except for transport facility, which is also high but lower than education facility criteria model. The comparison of R and RMSE for training and testing data are shown in Fig. 4.7.

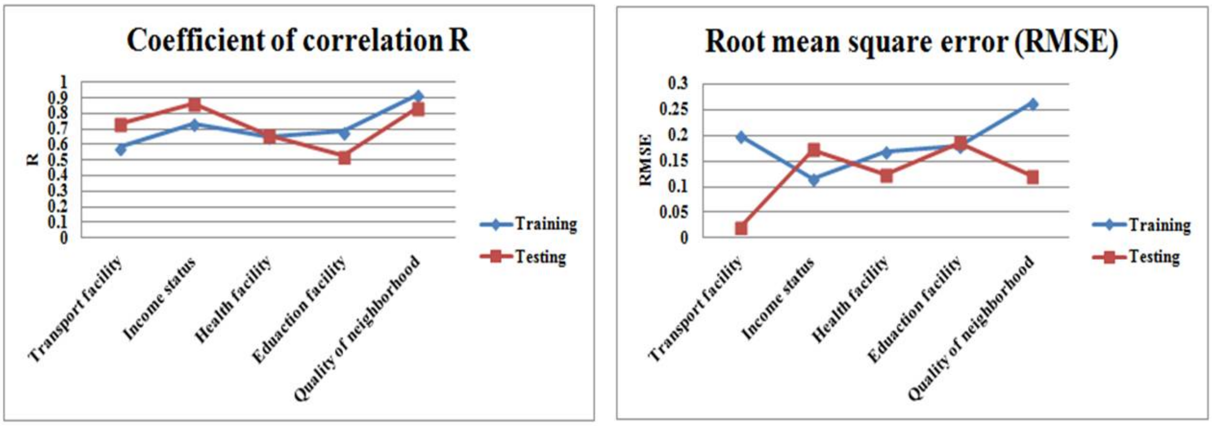


Fig. 4.7 Comparison of the Correlation coefficient (R) and RMSE for training and testing data

Fuzzy Delphi method is applied to assess the socio-economic impacts incurred by the rural inhabitants due to the deliverance of rural (PMGSY) roads. From the assessment of FDM, it can be observed that values of best non-fuzzy performance score for quality of neighbourhood criteria evaluated are in the range of 0.6 to 0.9, which illustrates that the scores fall in the range of high category to an ultimately high category on the non- fuzzy scale range as defined in Table 4.5. Therefore, it can be interpreted that the quality of life in the neighbourhood of the rural habitants is impacted positively, which can be considered as one of the significant impacts generated by the development of road infrastructure. Furthermore, it can also be observed from the best non-fuzzy performance scores of income status criteria that they vary in the range of 0.51 to 1.0, which resembles that the income status of rural habitants is impacted significantly. The income status criterion is defined by seven sub-criteria as mentioned in Table 4.2 above. From the results obtained for income status criteria model, it can be interpreted that inhabitants are being introduced to the new sources of income through increased production and better returns on the produce of agriculture or by other means.

Thus, there has been a positive change in income status criteria, leading to a significant change in the quality of neighborhood of rural habitants. Table 4.9 shows mean fuzzy weights and best non-fuzzy performance scores obtained for the quality of neighbourhood criteria.

Table 4.9 Mean fuzzy weights and best non-fuzzy performance score for quality of neighborhood criteria

S. No.	Mean fuzzy weights			Best non-fuzzy performance score	S. No.	Mean fuzzy weights			Best non-fuzzy performance score
1	0.56	0.67	0.71	0.65	15	0.65	0.75	0.79	0.73
2	0.56	0.67	0.71	0.65	16	0.65	0.75	0.79	0.73
3	0.56	0.67	0.71	0.65	17	0.65	0.75	0.83	0.74
4	0.65	0.75	0.83	0.74	18	0.60	0.70	0.75	0.68
5	0.75	0.85	0.89	0.83	19	0.82	0.93	0.95	0.90
6	0.80	0.90	0.93	0.88	20	0.75	0.85	0.89	0.83
7	0.71	0.80	0.85	0.79	21	0.75	0.85	0.89	0.83
8	0.59	0.70	0.76	0.68	22	0.64	0.75	0.80	0.73
9	0.71	0.80	0.85	0.79	23	0.70	0.80	0.87	0.79
10	0.48	0.60	0.51	0.53	24	0.65	0.75	0.83	0.74

11	0.55	0.65	0.72	0.64	25	0.85	0.95	0.96	0.92
12	0.49	0.60	0.69	0.60	26	0.66	0.75	0.81	0.74
13	0.59	0.70	0.76	0.68	27	0.85	0.95	0.96	0.92
14	0.61	0.70	0.79	0.70					

It has also been observed that education facility criteria has lower best performance non-fuzzy scores (ranging from low category to moderately low category) indicating that there is the least impact of road construction on overall education facility available to the residents, even though there is an increase in the percentage of school attendance of male and female students. The best non-fuzzy performance scores for transport and health facility range from low to moderately high category as shown in Table 4.10. Similarly, best non-fuzzy performance scores can be referred from Table 4.10 for all other criteria.

Table 4.10 Best performance score for criteria

S. No.	Best non-fuzzy performance score				
	Transport facility	Income status	Education facility	Health facility	Quality of neighborhood
1	0.51	0.51	0.32	0.61	0.65
2	0.43	0.73	0.33	0.61	0.65
3	0.37	0.62	0.45	0.42	0.65
4	0.44	0.83	0.34	0.54	0.74
5	0.44	0.89	0.20	0.66	0.83
6	0.57	0.76	0.48	0.42	0.88
7	0.39	0.58	0.55	0.49	0.79
8	0.56	0.88	0.33	0.68	0.68
9	0.56	0.73	0.44	0.65	0.79
10	0.57	0.61	0.49	0.54	0.53
11	0.57	0.74	0.43	0.47	0.64
12	0.65	0.70	0.50	0.34	0.60
13	0.45	0.70	0.51	0.42	0.68
14	0.46	0.70	0.37	0.39	0.70

15	0.51	0.70	0.33	0.54	0.73
16	0.51	0.70	0.33	0.54	0.73
17	0.39	0.88	0.34	0.58	0.74
18	0.61	0.92	0.34	0.39	0.68
19	0.34	0.79	0.40	0.43	0.90
20	0.65	0.52	0.43	0.25	0.83
21	0.67	0.65	0.52	0.47	0.83
22	0.52	0.86	0.44	0.38	0.73
23	0.73	0.65	0.30	0.35	0.79
24	0.57	0.90	0.44	0.42	0.74
25	0.45	0.83	0.50	0.47	0.92
26	0.56	1.04	0.53	0.38	0.74
27	0.51	0.94	0.46	0.30	0.92

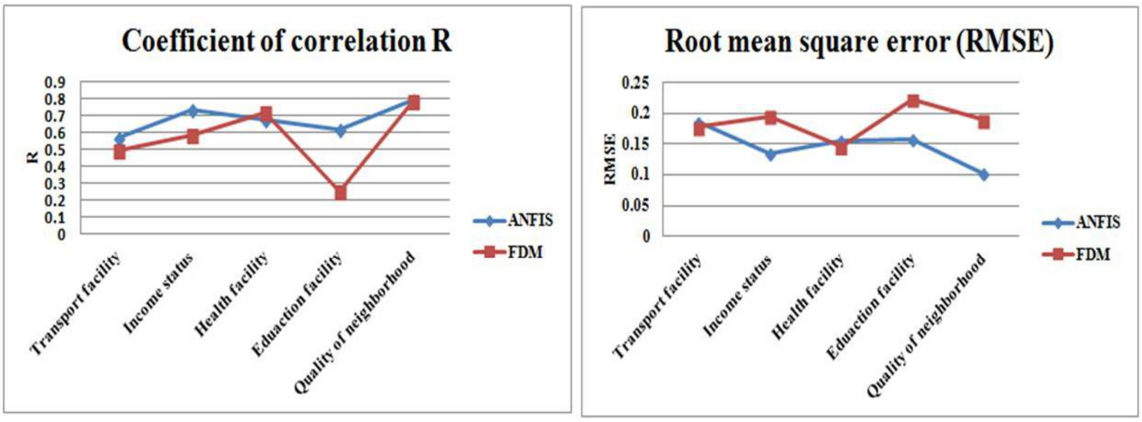


Fig. 4.8 Comparison of the Correlation coefficient (R) and RMSE for ANFIS and FDM models

Moreover, from the analysis based on model evaluation criteria, it is observed that ANFIS models developed for the study outperforms in comparison to that of models developed with FDM, which can be seen from Fig. 4.8. Furthermore, from the ANFIS analysis, the model developed for the health facility criteria is observed as the least impacted criteria, about 40% of habitations show moderately low impact on health and education facilities available to the inhabitants in the vicinity after the construction of PMGSY roads. One of the primary reasons for less impact on health facility and education facility criteria is the uneven distribution of facilities. Moreover, a significant impact is observed in case of quality of neighbourhood criteria, which signifies that with the advent of new roads there is a significant change in the quality of life. For better comprehension, the outcomes of ANFIS models are represented spatially by employing ArcGIS tool as shown in Figs. 4.9 to 4.11. The magnitude of impact due to the deliverance of PMGSY roads is depicted in the spatial representation as circles of varying sizes, larger the size of the circle indicates impact score is larger.

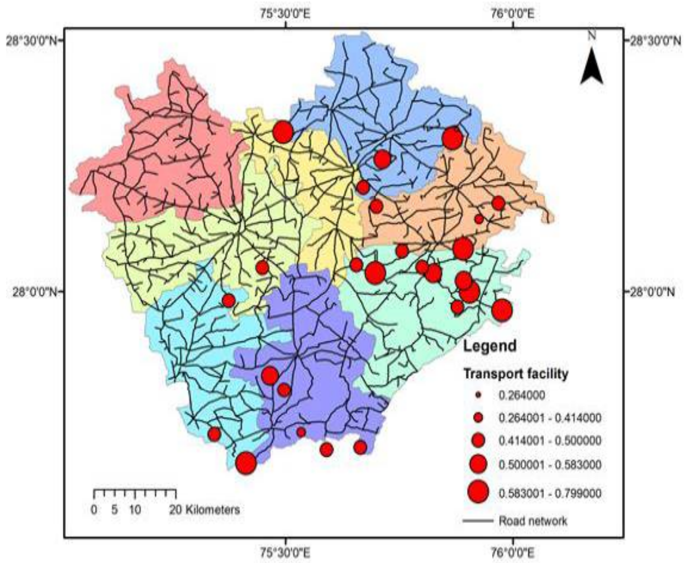


Fig. 4.9 Spatial representation of the impact of PMGSY roads on transport facility criteria

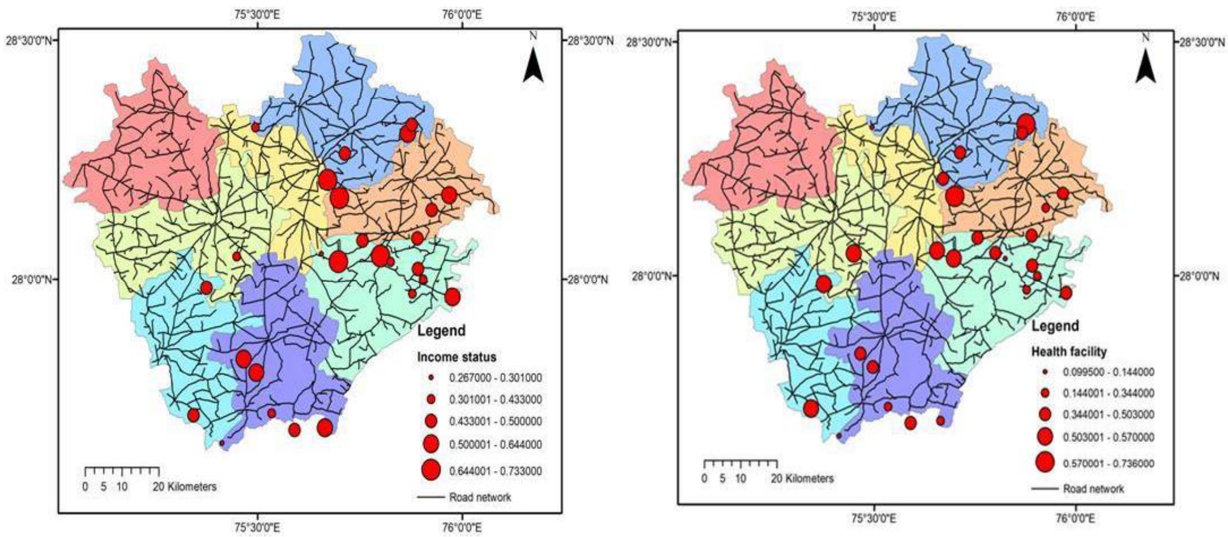


Fig. 4.10 Spatial representation of the impact of PMGSY roads on income status and health facility criteria

The change in the status of the criteria, which define socio-economic condition of the habitations, is shown in Figs. 4.12 to 4.14. This change in the status of the criteria is assessed by considering before and after condition of the criteria. It has been observed that the condition of income status has improved in all the habitations. However, highest income improvement has been observed in *Dhani Dalchinasi* and *Mukunda Deepchand Madiya* habitations in comparison with all remaining criteria considered for the study.

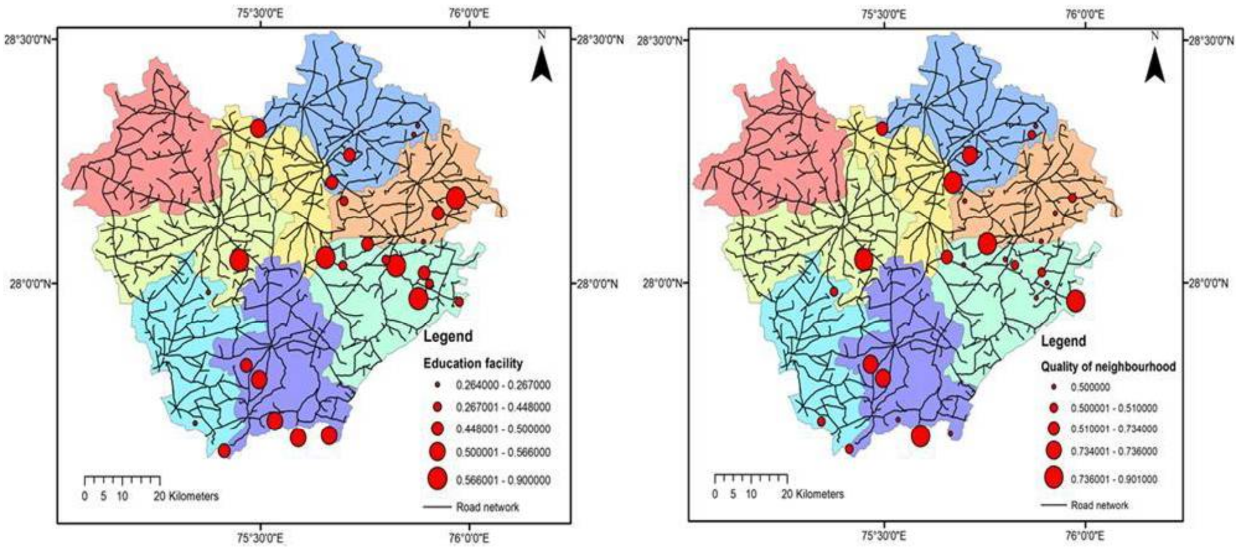
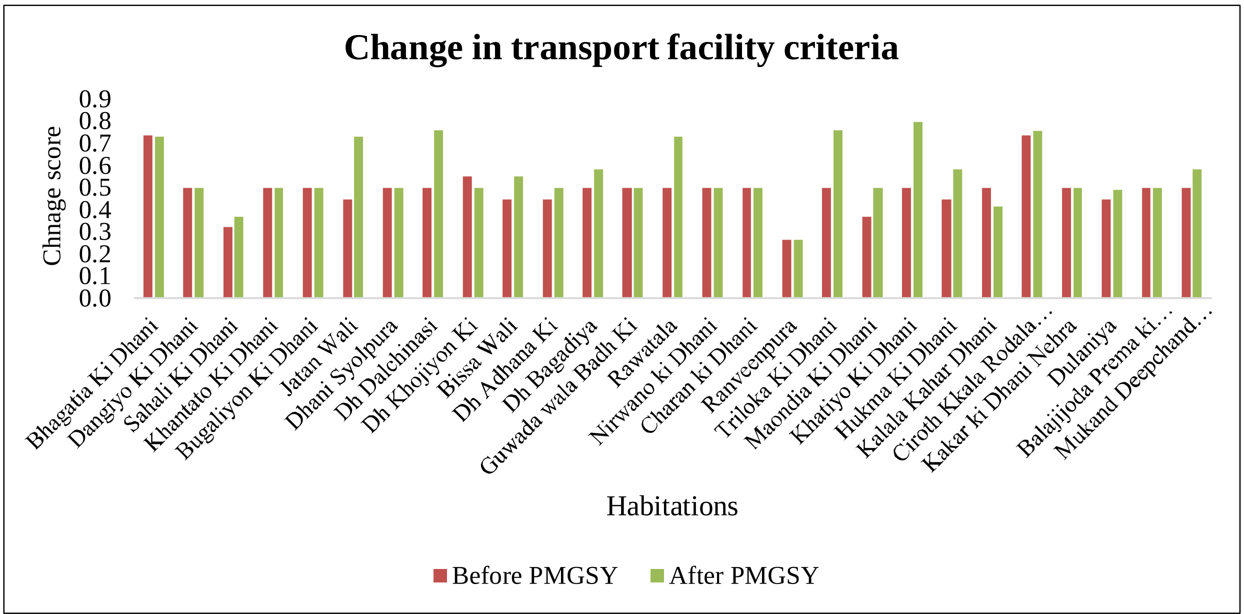


Fig. 4.11 Spatial representation of the impact of PMGSY roads on education facility and quality of neighborhood criteria

This implies that after the construction of rural roads the inhabitants avail income opportunities in much convenient manner as compared to their condition before road construction. This change is due to access to new income opportunities for the rural households. This is also evident from the change in the quality of neighborhood criteria. Improvement rural roads facilitated change in economic condition of the rural households, which has further led to improve their social status, encouraging them to involve social gatherings within and outside of their respective villages.

Moderate impact is observed in case of education facility and transport facility. The construction of PMGSY roads have not only reduced travel time and travel cost of the rural population but also could able to increase the number of enrolments into the education institutes and school attendance. As the availability of these facility in the vicinity of the habitation is scarce, the improvement can be magnified if these facilities are distributed evenly based on actual demand. However, the change in health facility criteria has been observed to be minimal in case of most of the habitations. In case of the habitations, viz., *Dhani Adhana Ki*, *Ranveerpura*, *Trilok Ki Dhani*, *Dhani Syolpura*, significant changes in the status of health facility criteria have been observed.



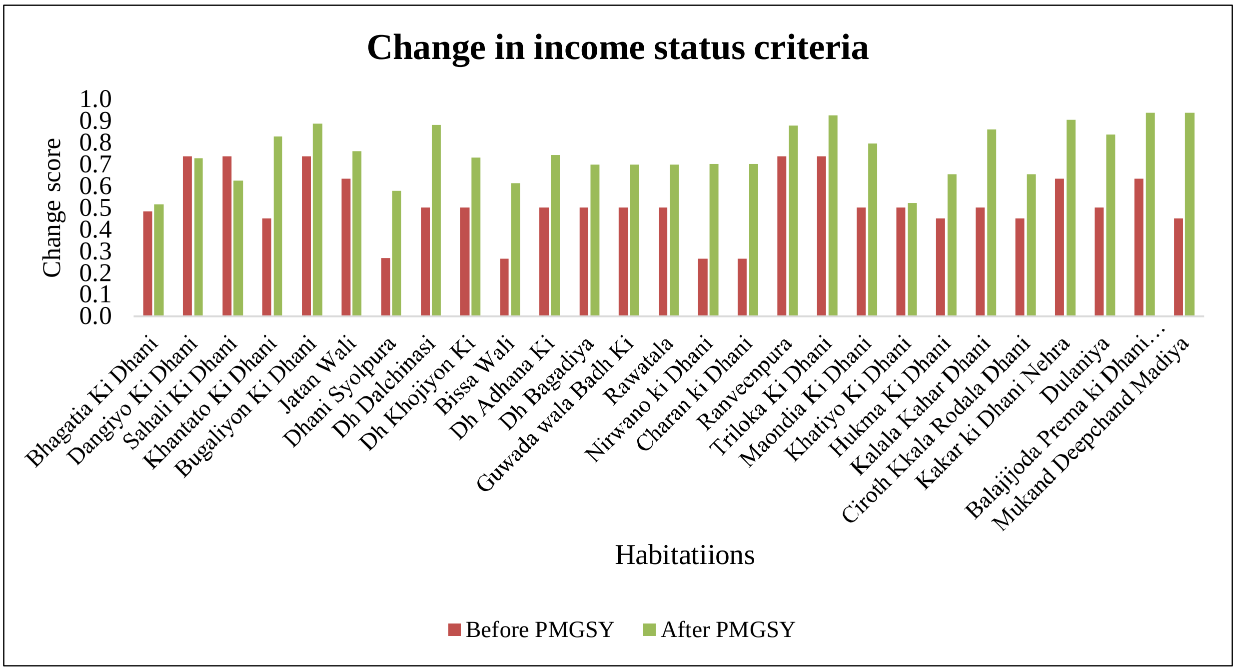
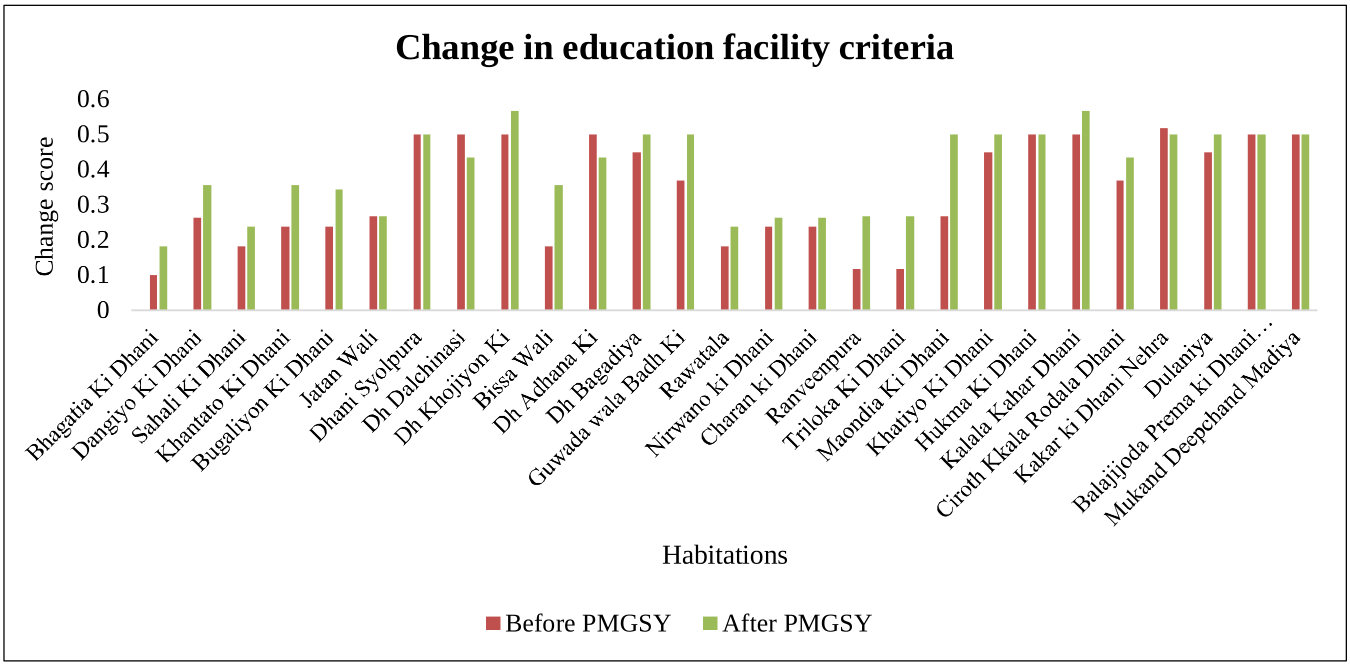


Fig. 4.12 Change in the transport facility and income status criteria in each of the habitation as the impact of PMGSY roads



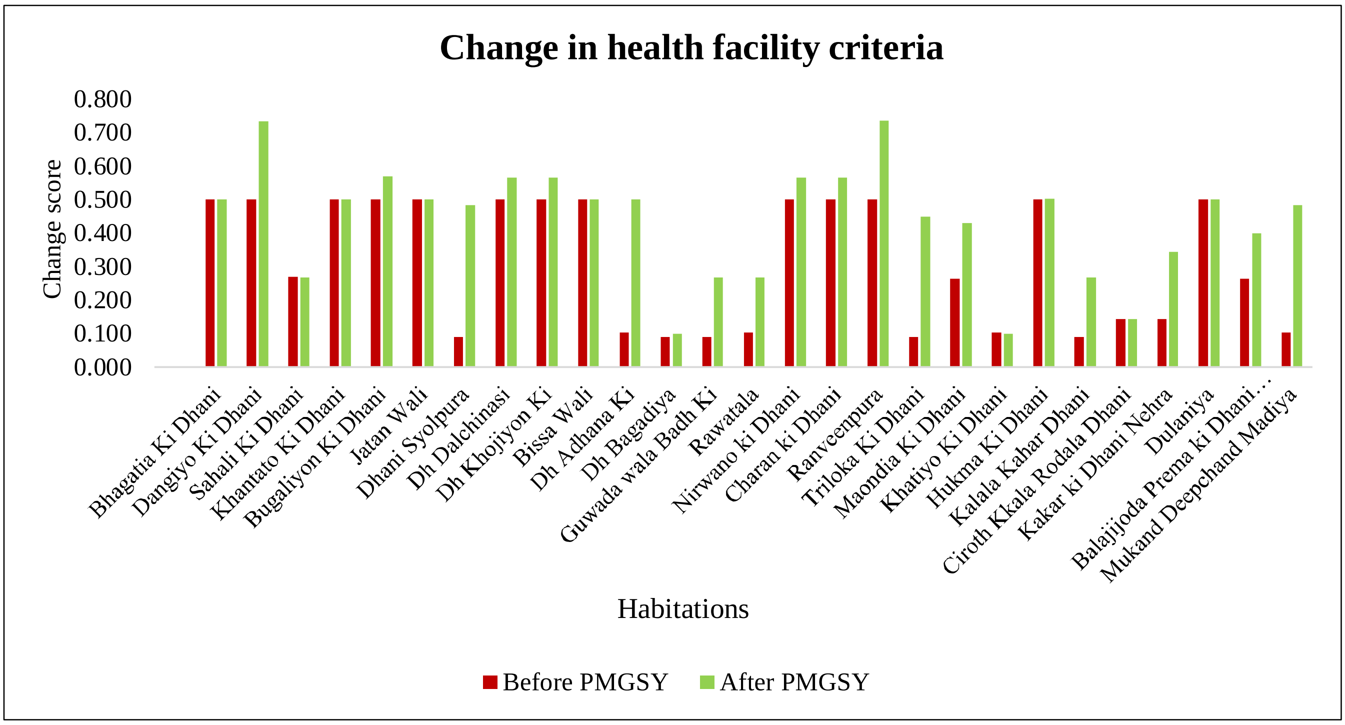


Fig. 4.13 Change in the education facility and health facility criteria in each of the habitation as the impact of PMGSY roads

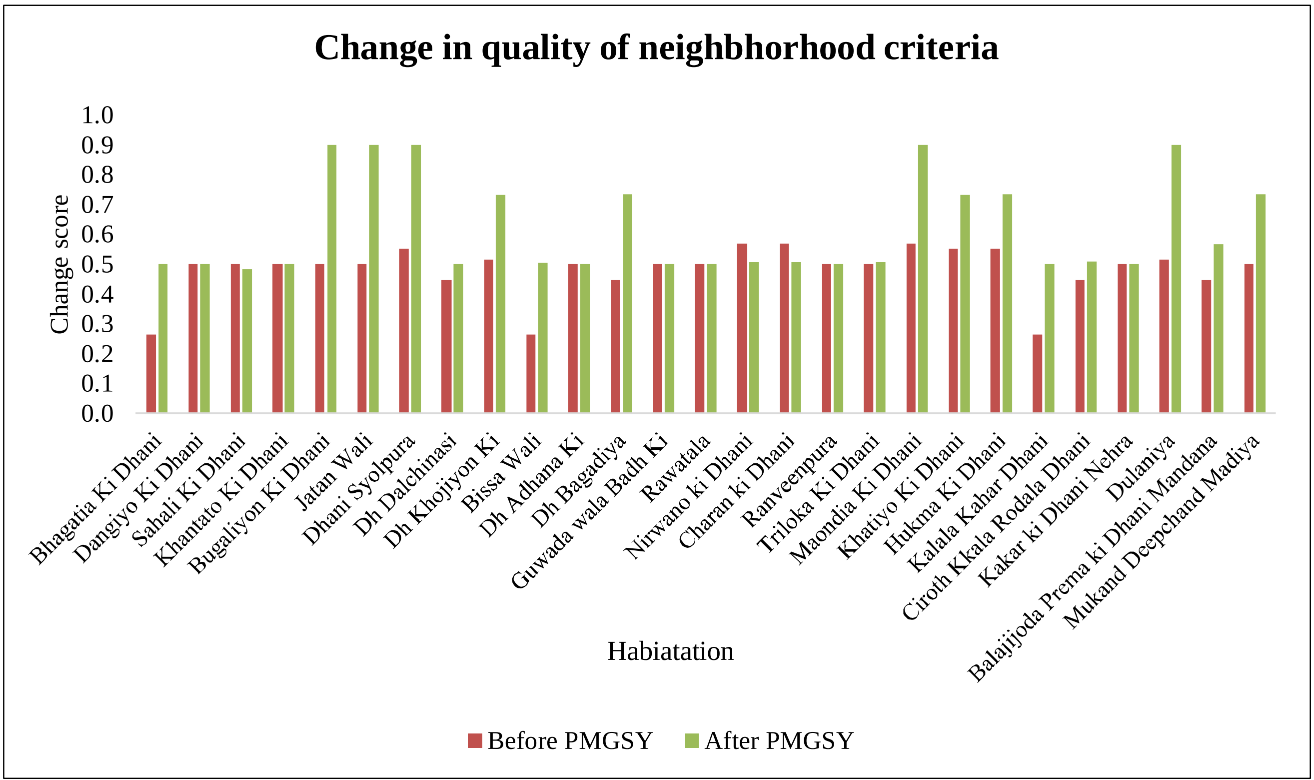


Fig. 4.14 Change in the quality of neighbourhood criteria in each of the habitation as the impact of PMGSY roads

4.6 Summary

The study presented in this chapter attempts to explore the impacts of construction of rural (PMGSY) roads with respect to various criteria, viz., transport facility, income status, education facility, health facility and quality of the neighborhood, which contribute in enhancing the socio-economic development of the rural population. One of the significant highlights of the study is the use of computational intelligence and FDM approach to identify the impacts. The techniques employed herein consider both qualitative and quantitative data simultaneously, as well as can ascertain significantly/critically impacted criteria. They also elucidate the possible scope of impacts caused in inclusive manner. The data collected for the study is based upon the focus group discussion, which is the perception of rural inhabitants. Total 27 habitations within six different blocks of Jhunjhunu district of Rajasthan state of India, are considered. The study also attempts to investigates the applicability of ANFIS technique based on subtractive clustering algorithm and fuzzy Delphi method for evaluating the socio-economic impacts of rural roads on the target population.

Findings of the proposed methodology reveal that the income status and quality of neighborhood criteria show significant impacts (Figs. 4.12 to 4.16), whereas health and education facility criteria show a lower impact. The models developed herein for income status and quality of neighbourhood criteria perform well using ANFIS and FDM modelling respectively. They are found to be effective in evaluating the necessary knowledge about the impacts instigated by the construction of the rural (PMGSY) roads. It depicts that quality of neighbourhood and income show positive impacts due to the deliverance of rural road infrastructure. Owing to the positive impacts, it can be inferred that the habitants are able to avail different income opportunities, which in turn is assisting them to have stabilized income source and helping them to raise their social status.

However, it is observed that the models for health and education facility criteria show lowest scores, which replicate less impact on the status of these facilities, available to inhabitants. Thus, indicating need of even distribution of social facilities available to rural inhabitants. Therefore, from value addition point of view, the analysis presented in this study will provide basis and understanding for decision-making authorities for implementing schemes and policies for enhancing the status of least impacted criteria. It has been observed that the quality of neighbourhood and income status are sensitive to the improvement of rural roads, followed by a considerable moderate impact on transport facility. The results of the proposed methodology may help in assisting the policy and decision makers to have a better view of ground condition after the deliverance of roads and to intensify their focus on accomplishing the overall objective of rural development.

All-important findings of this study suggested that ANFIS models outperforms in comparison with the model developed with FDM approach. Also, the developed model (ANFIS) can quantify the qualitative information, which comprehensively is of subjective nature and can handle real-world problem associated with uncertainties as well as it is time-cost effective. It also adds up as a significant technique to the SEIA literature.