Developing a Fuzzy Logic-Based Approach to Determine Prosperity for Smart City Policymaking

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Abstract: Prosperity measurement is important for smart cities because it allows city officials and policymakers to understand the economic well-being of the city and its residents. This information can then be used to make informed decisions about how to allocate resources and develop policies that will improve the overall prosperity of the city. Additionally, prosperity measurement can also be used to track progress and evaluate the effectiveness of existing policies and programs. This can help to ensure that resources are being used in the most efficient and effective way possible. Overall, prosperity measurement is a key tool for creating a more equitable, sustainable, and prosperous city for all residents. In this paper, we introduce an intelligent model for smart cities utilizing fuzzy logic to help enhance policymaking and help objectively assess the effectiveness of smart cities. The proposed FIS-based expert system can classify a smart city's prosperity as satisfied, good, excellent, or exceptional.

Keywords: Quality of life, social welfare, social inequality, economic inequality, Mamdani Fuzzy logic

1 Introduction:

Prosperity in the context of smart cities refers to the overall well-being and economic health of the city and its residents. This includes factors such as economic growth, job opportunities, income levels, and access to services and resources. A smart city that is prosperous will have a strong and diverse economy, with a mix of different industries and businesses that provide a range of job opportunities for residents (Lazaroiu, 2018). Additionally, residents will have access to education and training opportunities that allow them to develop the skills they need to succeed in the modern economy. The prosperity of a smart city also depends on the standard of living of its citizens, which is often linked to the level of income, access to quality housing, healthcare, and other services (Fatima, 2019). Prosperity measurement is an important aspect of the development and management of smart cities as it helps to understand the economic well-being of the city and its residents, and identify areas of strength and weakness. By regularly measuring key indicators of prosperity, cities can see how their policies and programs are impacting the economic well-being of residents and make adjustments as needed. Another important aspect of prosperity measurement is that it can help to identify disparities and inequalities within a city (Nadeem, 2019). By identifying and addressing these disparities, smart cities can work towards creating a more equitable and inclusive environment for all residents.

There is a need to measure prosperity with the help of an artificial intelligence (AI) approach because it can provide more accurate and comprehensive results than traditional methods. An AI approach to measuring prosperity can help to automate the data collection process, making it more efficient and cost-effective (Salcedo, 2022). It can also help to analyze large and complex datasets in a shorter amount of time, providing more accurate and up-to-date information on the economic well-being of a city and its residents. An AI approach can also help to make the data more accessible to city officials, policymakers, and residents by providing interactive dashboards and visualizations (Djahel, 2015). This can make it easier for stakeholders to understand the data and identify areas that need attention. In our proposed study fuzzy logic systems can be used to measure prosperity of smart cities by utilizing the ability of fuzzy logic to handle uncertainty and imprecision in the input data. Fuzzy logic systems can help to evaluate the economic well-being of a city by using multiple indicators such as GDP, unemployment rate, income levels, and others. These indicators can be assigned fuzzy membership values, which can then be used to calculate a final prosperity score for the city. Fuzzy logic systems can also be used to analyze and interpret large and complex datasets, such as data from social media, sensors, and other sources, providing a more comprehensive understanding of the economic well-being of the city and its residents (Lei, 2021). Fuzzy logic systems can also be used to identify patterns and correlations within the data, for example, by identifying areas of the city with higher or lower prosperity scores, or by identifying demographic groups that may be more or less affected by economic issues. Fuzzy logic systems can also be used to make predictions and forecast economic trends, which can be useful for smart city planning, such as anticipating the demand for housing, job opportunities, and identifying potential areas for growth (Buyukozkan, 2019). Prosperity is a multidimensional concept that can be measured using various indicators such as economic growth, employment, standard of living, quality of life, etc. Using fuzzy logic to measure prosperity would involve defining input and output variables that represent these indicators.

Input variables:

- Economic growth: Measured by indicators such as gross domestic product (GDP) per capita, GDP growth rate, etc.
- Employment: Measured by indicators such as unemployment rate, labor force participation rate, etc.
- Social welfare: Measured by indicators such as poverty rate, income inequality, access to education and healthcare, etc.
- Quality of life: Measured by indicators such as life expectancy, crime rate, and access to green spaces, etc.

Output variables:

- Prosperity levels: A categorical output variable that classifies the level of prosperity into different categories such as high, medium, low, etc.

Once the input and output variables are defined, fuzzy logic can be used to create a model that takes the input variables as input and produces the output variables as output. The model would use fuzzy logic rules and membership functions to map the input variables to the output variables.

2 Literature Review:

In order to understand the applications of smarter policymaking and the contribution of fuzzy Logic to maximize cognitive capacities in one way or another, many proposed works from previous literature have been examined in this section.

Smart cities are increasingly embracing home-based healthcare systems. When choosing a diagnosis and the appropriate course of action at the moment, timely information regarding the health condition of individuals with chronic heart disease might be very important. For out-of-hospital follow-up and monitoring of patients with chronic heart disease who are under stable conditions, the author suggests a home healthcare system based on fuzzy logic. The suggested system may offer timely resources and a complement to the current healthcare systems, assisting practitioners in effectively treating cardiac patients who were living alone at home (Hussain, 2016).

To improve the chances of a casualty's survival, an Emergency Vehicle must move faster. Construction projects, strikes, and accidents may all be avoided with an effective vehicle navigation strategy. The Internet of Things (IoT) network model for emergency vehicle transportation is proposed in this study utilizing a fuzzy logic-based data fusion approach. By taking into consideration sensory data as well as the population density of humans from the population, the data fusion-based system predicts the location of target vehicles. In this way the quickest, most congested-aware path is suggested to a driver in an emergency vehicle while they go to a hospital (Rout, 2020).

An essential component of a smart city is general lighting, which requires frequent maintenance and inspection of lighting conditions. Thousands of lights are located in smart cities, making it wasteful in terms of time, money, and energy to physically inspect each one individually. In this paper, the author suggests a method for managing city lighting servicing that can both supervise from anywhere and forecast the quality of the light using fuzzy logic (Al Kindhi, 2021). The proposed method makes use of a microcontroller in Internet of Things (IoT) devices and a fuzzy logic technique to forecast how well or poorly lighting would work.

By analyzing the enormous amount of data generated by people, which spans a huge variety of domains, new app, and technology infrastructures appear to improve information and communications technologies, enabling cities to embrace their services more proficiently. This makes a significant contribution to the effective solution of ecological and socioeconomic concerns. In order to achieve this, authors suggest a system that makes use of a distributed and streaming data processing structure along with the application of fuzzy logic to categorize described thoughts in real-time, providing insight to government officials and increasing people's involvement in the creation of their smart societies (Mohamed, 2019).

An essential need for predicting and measuring uncertain contaminants is the capability to forecast pollution in response to changing environmental circumstances. Many environmental engineering issues can be solved using fuzzy inference algorithms, and they have had positive outcomes. Given that the pollution concentration in certain locations is unpredictable or imprecise, the author suggests an intelligent system based on fuzzy logic to forecast the Air Quality Index in the relevant area (Riyaz, 2018).

Flooding is a common problem in urban areas due to a variety of factors including heavy precipitation, alterations in land usage, and a comparatively heavy rainfall. Knowing the factors that cause flooding, particularly rainfall and air temperature is one approach to prepare for floods. The connection and intensity between temperature and rainfall were examined by the author in order to determine whether or not flooding will occur in the city during that month. For this purpose they proposed the mamdani fuzzy logic system (Al Kindhi B. a., 2021).

3 Proposed Methodology:

A fuzzy logic decision making system is a type of artificial intelligence system that uses fuzzy set theory to make decisions. It is a mathematical framework for dealing with uncertainty and imprecision and is based on the idea that concepts can be partially true, rather than either true or false (Wang, 2021). Mamdani fuzzy logic is particularly useful in situations where the system requires human knowledge and experience to be incorporated into the decision making process and where there is a need to handle uncertainty and imprecision in the input data. Mamdani fuzzy logic differs from classical binary logic in that it allows for degrees of truth between 0 and 1, rather than just binary true or false values. This means that in Mamdani fuzzy logic, a concept can be partially true rather than just true or false (Iatrellis, 2022). This allows for more nuanced and flexible decision making, particularly in situations where the input data is uncertain or imprecise. In Mamdani fuzzy logic, the inputs are transformed into fuzzy sets using membership functions and then processed using fuzzy inference rules to produce a fuzzy output. The membership functions are used to determine the degree of membership for each element in the fuzzy set, and the fuzzy inference rules are used to determine the relationship between the inputs and the outputs. **Figure 1** represents the working model of our proposed fuzzy logic system.

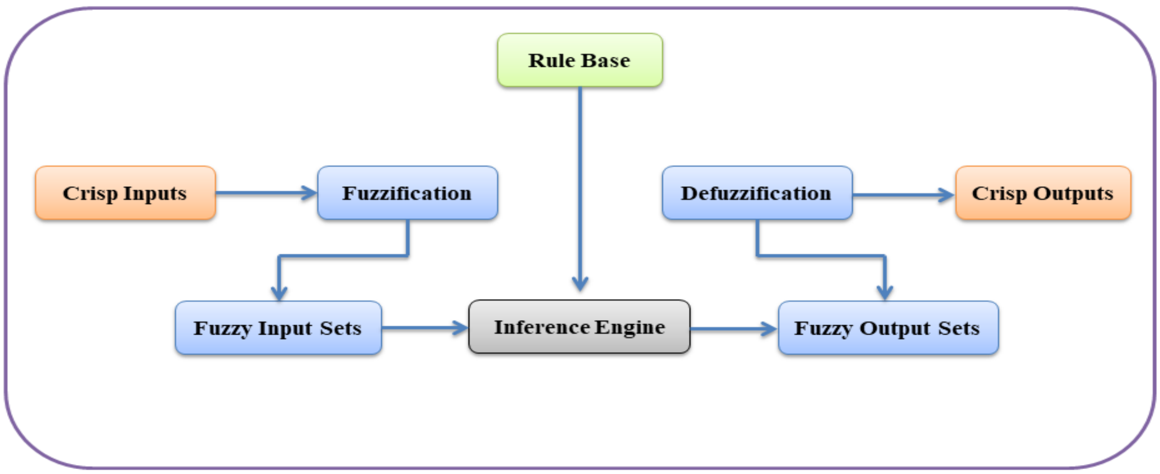

Figure 1: Fuzzy logic model

The fuzzy output is then defuzzified, or transformed back into a crisp value, which can be used for decision making. Defuzzification is typically performed using a method such as the center of gravity or the mean of maximum (Karyaningsih, 2020). These methods calculate the crisp value that best represents the fuzzy output based on the membership functions. For example, consider a simple two-input, one-output Mamdani FLC with the following rules:

IF x1 is A1 AND x2 is A2 THEN y is B
IF x1 is A3 AND x2 is A4 THEN y is C

A fuzzy logic-based approach can be used to determine the prosperity for policymaking of a smart city. Prosperity can be considered as a multi-faceted concept, encompassing aspects such as economic growth, social well-being, and environmental sustainability. The factors that assess a city's prosperity in our suggested research, such as GDP, Education, Quality of Life, and Employment, will be used as input variables. Set rules as desired to determine the prosperity of a smart city are shown below:

Employment: Un-employed, Workers, Employed
Quality of life: Crime rate, expectancy, access to green spaces (ATGS).

GDP: Low, Medium, High
Education: High School, Bachelor, Post-Graduate, Doctorate

Once the key factors have been identified, membership functions can be defined for each factor to represent its contribution to prosperity. For example, a high GDP and low crime rate would have a high degree of membership in the "prosperous" set, while a low GDP and high crime rate would have a low degree of membership. Be aware that we built a smart decision based system with four different inputs, including GDP, education, quality of life, and employment. The FIS editor inputs and output variables of our suggested intelligent system are shown in **Fig. 2**.

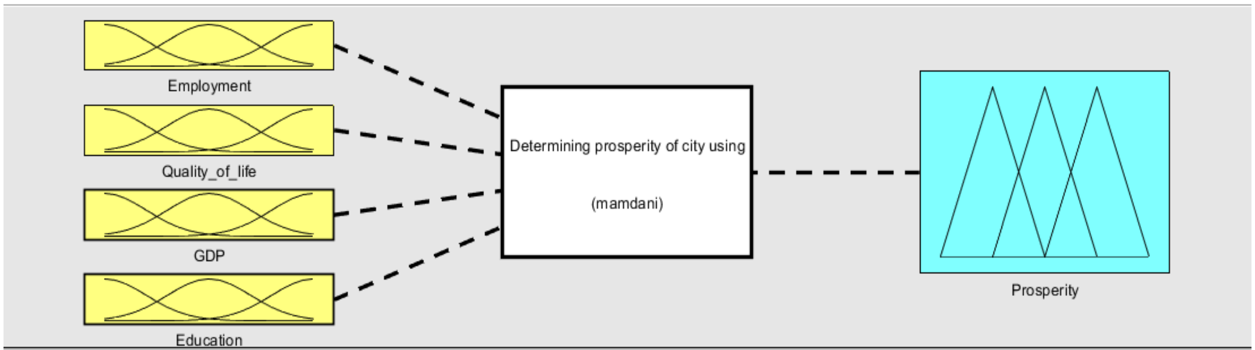

Fig 2: FIS editor of proposed system

3, 3.1 Input Variable:

Every provided variable receives linguistic values according to the fuzzifier association with the specified crisp values for input stimuli at a certain level. The inference engine uses fuzzy standards, consequences, and inference to replicate human decision-making in fuzzy logic. The four input variables and one output variable which is the prosperity of a smart city, trapezoidal membership functions created using MATLAB R2020b are shown in **figure 3a, 3b, 3c, 3d.**

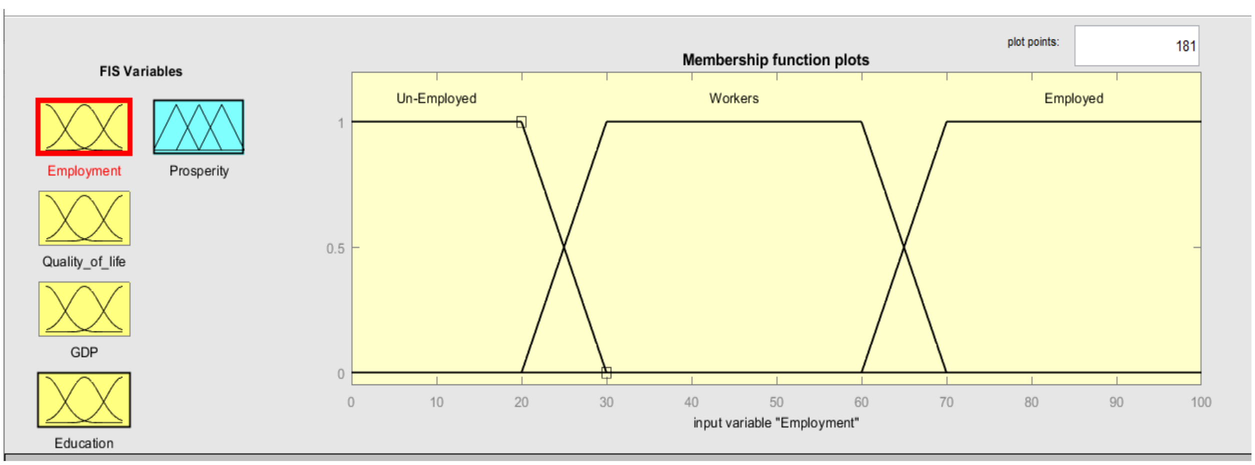

Fig 3a: Membership functions for Input "Employment"

Employment: Un-employed, Workers, Employed

$$\mu_U(E) = \begin{cases} \dfrac{30-E}{30-20} (20 \le E \le 30 \end{cases}$$

$$\mu_W(E) = \begin{cases} \dfrac{E-20}{30-20} & (20 \le E \le 30 \\ \dfrac{70-E}{70-60} & (60 \le E \le 70 \end{cases}$$

$$\mu_E(E) = \begin{cases} \dfrac{E-60}{70-60} (60 \le E \le 70 \end{cases}$$

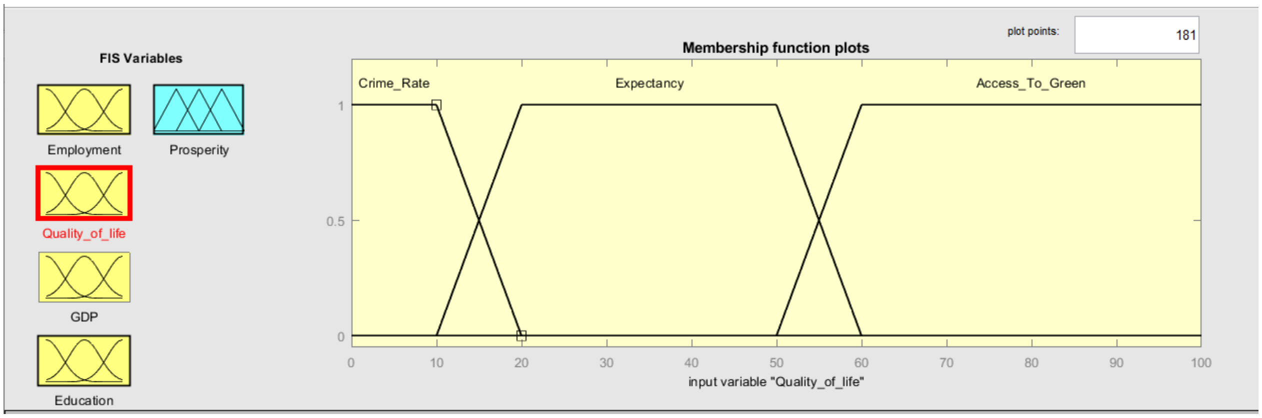

Fig 3b: Membership functions for Input “Quality of Life”

Quality of life: Crime rate, expectancy, access to green spaces (ATGS).

$$\mu_{CR}(Q) = \begin{cases} \dfrac{20-Q}{20-10} (10 \le Q \le 20 \end{cases}$$

$$\mu_E(Q) = \begin{cases} \dfrac{Q-10}{20-10} & (10 \le Q \le 20 \\ \dfrac{60-Q}{60-50} & (50 \le Q \le 60 \end{cases}$$

$$\mu_{ATG}(Q) = \begin{cases} \dfrac{Q-50}{60-50} (50 \le Q \le 60 \end{cases}$$

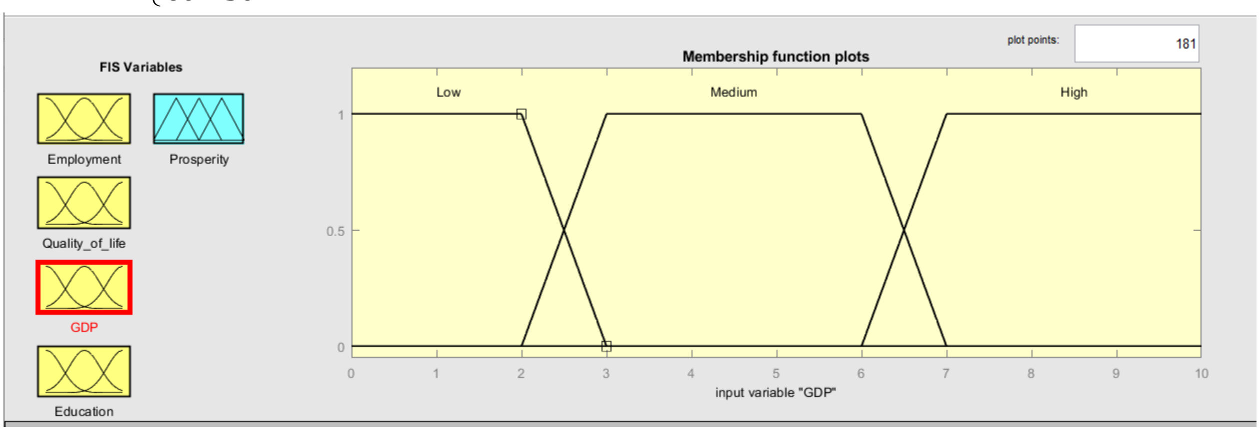

Fig 3c: Membership functions for Input “GDP”

GDP: Low, Medium, High

$$\mu_L(G)=\begin{cases}\dfrac{3-G}{3-2}(2\le G\le 3\end{cases}$$

$$\mu_M(G)=\begin{cases}\dfrac{\dfrac{G-2}{3-2}}{\dfrac{7-G}{7-6}} & \begin{matrix}(2\le G\le 3\\(6\le G\le 7\end{matrix}\end{cases}$$

$$\mu_H(G)=\begin{cases}\dfrac{G-6}{7-6}(6\le G\le 7\end{cases}$$

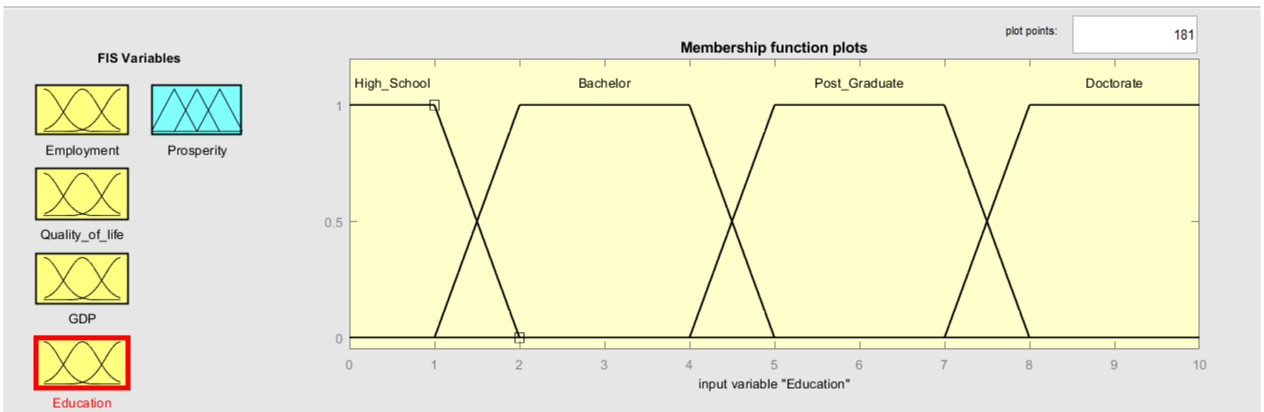

Fig 3d: Membership functions for Input "Education"

Education: High School, Bachelor, Post-Graduate, Doctorate

$$\mu_{HS}(E)=\begin{cases}\dfrac{2-E}{2-1}(1\le E\le 2\end{cases}$$

$$\mu_B(E)=\begin{cases}\dfrac{\dfrac{E-1}{2-1}}{\dfrac{5-E}{5-4}} & \begin{matrix}(1\le E\le 2\\(4\le E\le 5\end{matrix}\end{cases}$$

$$\mu_{PG}(E)=\begin{cases}\dfrac{\dfrac{E-4}{5-4}}{\dfrac{8-E}{8-7}} & \begin{matrix}(4\le E\le 5\\(7\le E\le 8\end{matrix}\end{cases}$$

$$\mu_D(E)=\begin{cases}\dfrac{E-7}{8-7}(7\le E\le 8\end{cases}$$

3, 3.2 Output Variable:

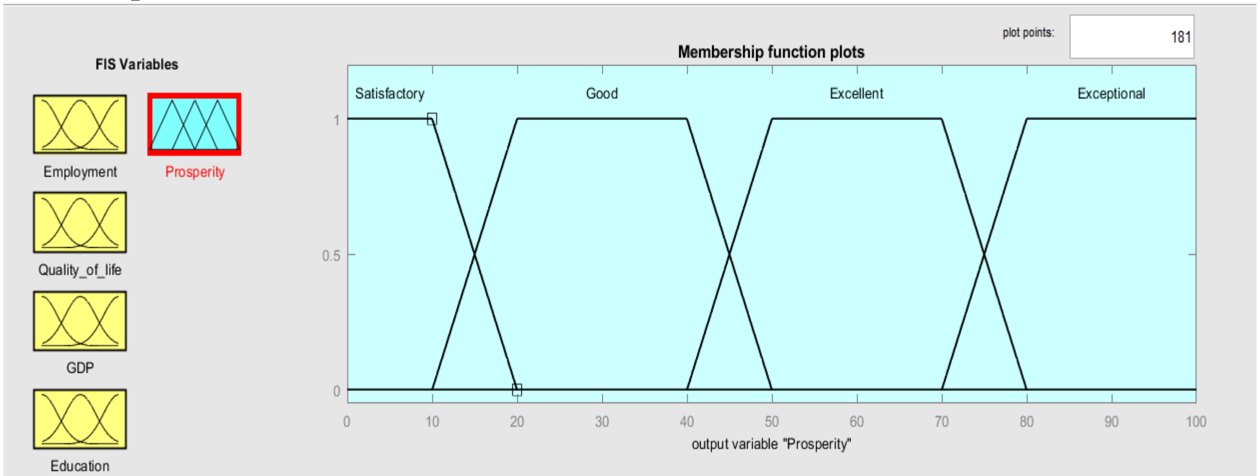

Fig 4: Membership functions for Output "Prosperity of smart city"

Prosperity of smart city: Satisfactory, Good, Excellent, and Exceptional

$$\mu_S(P) = \left\{ \frac{20-P}{20-10} (10 \le P \le 20 \right.$$

$$\mu_G(P) = \begin{cases} \dfrac{P-10}{20-10} & (10 \le P \le 20 \\ \dfrac{50-P}{50-40} & (40 \le P \le 50 \end{cases}$$

$$\mu_E(P) = \begin{cases} \dfrac{P-40}{50-40} & (40 \le P \le 50 \\ \dfrac{80-P}{80-70} & (70 \le P \le 80 \end{cases}$$

$$\mu_{EX}(P) = \left\{ \frac{P-70}{80-70} (70 \le P \le 80 \right.$$

3, 3.3 Inferences:

25 inference rules are developed in accordance with the observational analysis of the correlation between the fuzzy input and fuzzy output planning and the aggregation phase of the outcome. Some of the inferential rules in tabular form are shown in **Table 1**. A crucial element of fuzzy logic systems is fuzzy inference rules, which offer a means of mapping input values to output values in accordance with a preset set of rules. The knowledge and skills of domain-specific that have a thorough grasp of the system being modeled are intended to be captured by these rules (Bhardwaj, 2022). The most common format for a fuzzy inference rule is an "if-then" statement, where the "if" section, also known as the antecedent, specifies the circumstances under which the rule applies, and the "then," also known as the consequent, specifies the action that should be performed when the rule is activated.

Table 1: Some of the inference rules

	Employment	**Quality of Life**	**GDP**	**Education**	**Prosperity**
Rule 1	Un-Employed	Crime Rate	Low	High School	Satisfactory
Rule 5	Un-Employed	Expectancy	Medium	High School	Satisfactory
Rule 7	Workers	Crime Rate	Medium	Bachelor	Good
Rule 11	Workers	Expectancy	Low	Bachelor	Good
Rule 15	Workers	Expectancy	Medium	Post Graduate	Excellent
Rule 17	Employed	Access to Green	High	Post Graduate	Excellent
Rule 20	Employed	Expectancy	Medium	Doctorate	Exceptional
Rule 25	Employed	Access to Green	High	Doctorate	Exceptional

From straightforward control systems to more intricate systems like decision-making, image processing, and natural language processing, fuzzy inference rules may be used to describe a variety of systems (Abuga, 2021). These systems often use fuzzy sets to specify input variables, allowing either uncertain or imprecise norms. On the other hand, depending on the needs of the system, the output variables may be specified utilizing crisp or fuzzy sets. The 25 inferences rule of our suggested system is shown in **Fig. 5**.

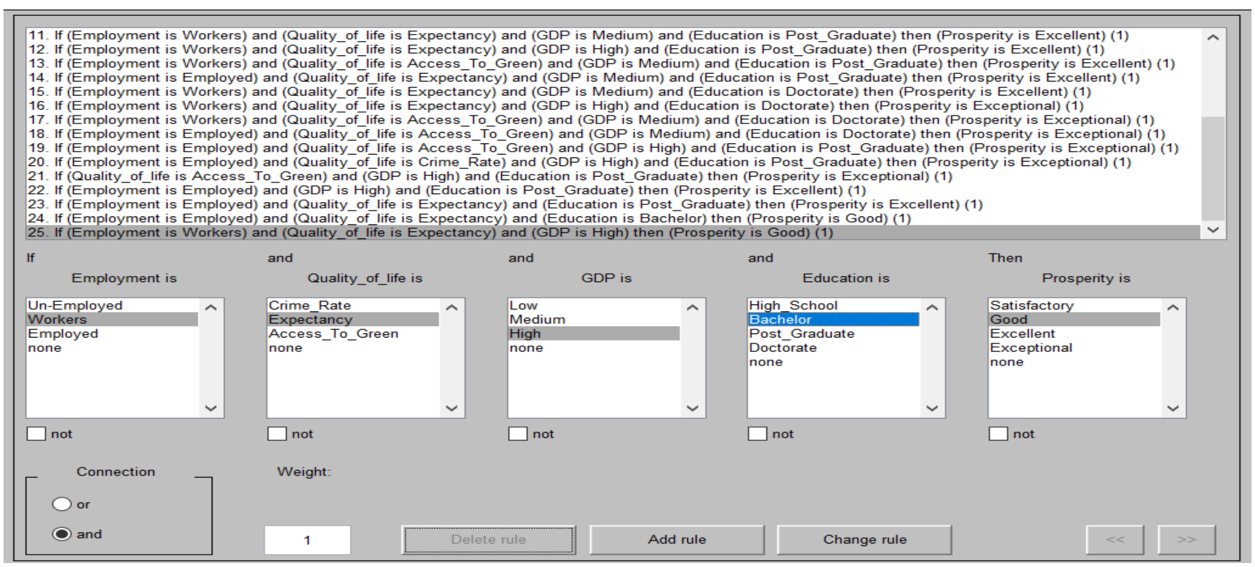

Fig 5: Fuzzy inferences rules

When the fuzzy inference rules are established, they may be used to influence the system's behavior and make judgments depending on the input values. A fuzzy inference engine a software application that is in charge of assessing the rules and finding the proper output values depending on the input values, is often used to do this (Costa, 2017).

Because they offer a means of encapsulating the knowledge and proficiency of subject-matter specialists in the format of if-then statements, fuzzy inference rules are an effective tool for modeling complicated systems. These rules may be used in a variety of systems, from basic control systems to more complicated systems like decision-making and natural language processing, to map input values to output values depending on a set of established rules. Fuzzy inference rules can be represented graphically in the form of a decision tree, which provides a visual representation of the relationships between input values and output values.

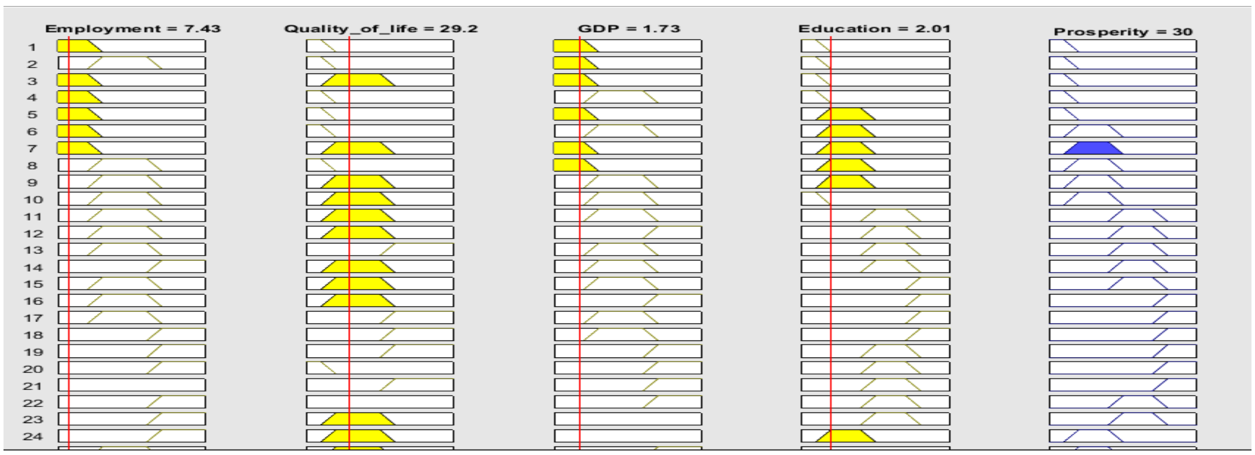

Fig 6: Rule base indicate prosperity in good form

This can make it easier to understand the behavior of a fuzzy logic system and to modify the rules as needed. Four different input factors are employed in the suggested methodology to evaluate prosperity and determine smart city strategies. These factors entirely influence a city's level of prosperity; if the suggested input variables have low values, the city's prosperity is not doing well. According to the rule basis shown in **Fig. 6**, the employment rate, education levels are very low and quality of life, GDP are much better than the preceding two variables. As a result, the prosperity rate is shown to be in good shape. **Fig. 7** demonstrates that the GDP is medium, the employment rate is high, the quality of life is outstanding, and education is also in excellent shape, so the prosperity rates are in excellent form.

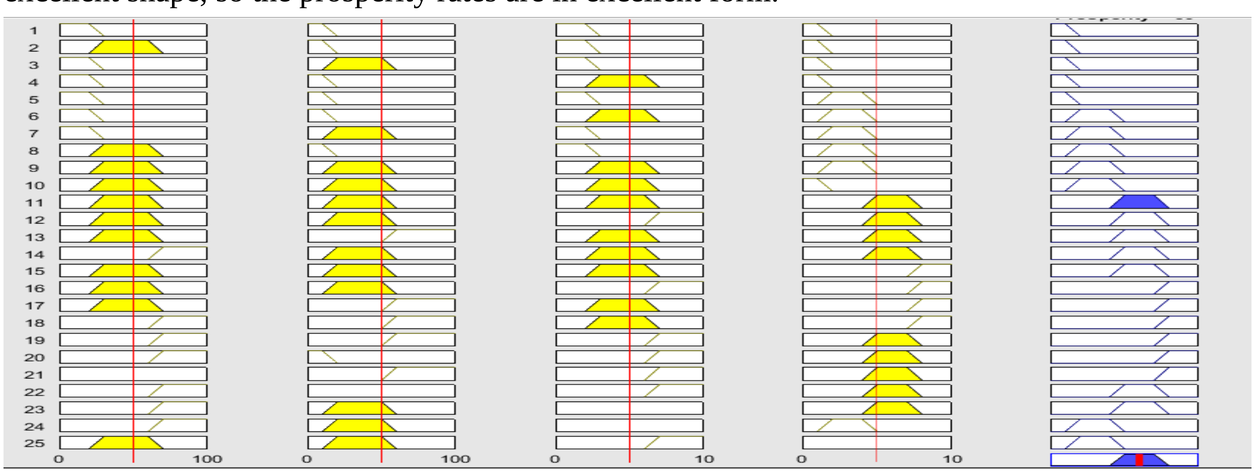

Fig 7: Rule base indicate prosperity in excellent form

3, 3.4 Surface Graph:

In Mamdani fuzzy logic, a surface graph is a graphical representation of the relationship between the input and output variables of a fuzzy system. The surface graph is created by plotting the output variable on the vertical axis and the input variable on the horizontal axis (Rahmani, 2022). The fuzzy sets for the input variable and the output variable are then represented on the surface graph as regions of different shades or colors. The surface graph is created by using the inference rules in the rule base, and it shows how the output variable changes as the input variable changes. It shows the mapping between the input and output variables, and how the fuzzy sets for the input variable and the output variable are related to each other.

In a surface graph, the X and Y axes represent the two dimensions of the domain. The Z-axis represents the values or the outcome of the function being plotted. The values of the function are displayed on the surface as a series of interconnected points that form a continuous surface. The surface can be displayed in a variety of ways, such as a wireframe, a shaded surface, or a combination of both. **Fig 8** shows the surface graph based on GDB and employment rate. A surface graph can be used to visualize the relationship between Gross Domestic Product (GDP) and the status of a city in terms of its prosperity. GDP is a measure of the total value of goods and services produced by a city over a certain period of time and are widely used as an indicator of economic prosperity. In a surface graph, the X-axis can represent the employment rate of a city, the Y-axis can represent the GDP, and the Z-axis can represent the status of a city. The surface would display the relationship between these three variables. For example, cities with higher GDP levels may generally have higher employment rates and higher status, while cities with lower GDP levels may have lower employment rates and lower status.

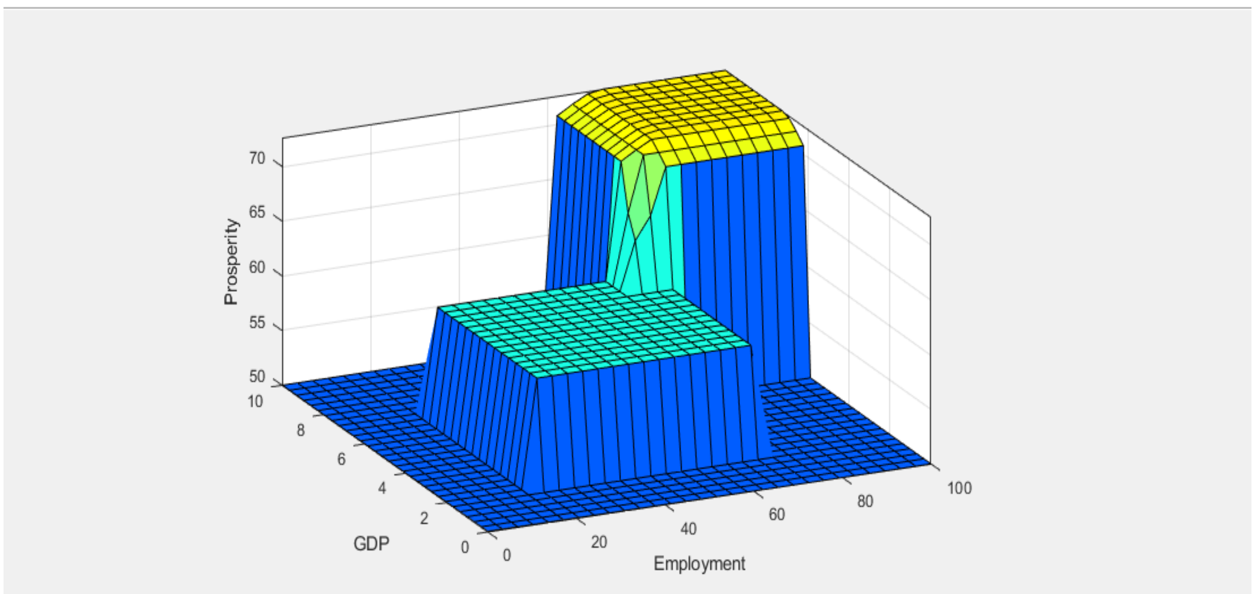

Fig 8: Surface graph based on employment and GDP

A city's quality of life may be assessed based on a number of variables, including the level of living, accessibility to healthcare and education, and the crime rate. **Fig 9** shows the surface graph based on GDP and quality of life. In **fig 9** surface graph, the X-axis can represent the quality of life, the Y-axis can represent the GDP of a city, and the Z-axis can represent the prosperity of a city. The relationship between these three factors would be visible on the surface.

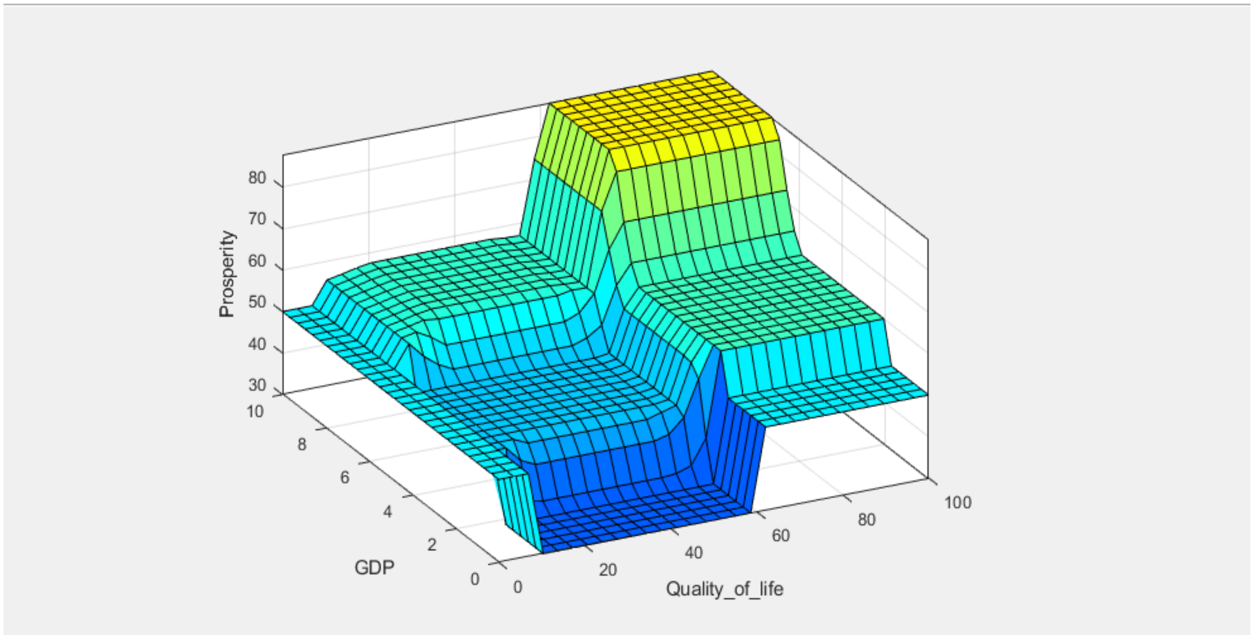

Fig 9: Surface graph based on Quality of life and GDP

Cities with higher GDPs could, for instance, have better quality of life overall and more prosperity, whereas cities with lower GDPs might have worse quality of life overall and less prosperity. By providing a visual representation of the data, surface graphs help researchers and policy makers to identify trends, patterns, and correlations that may not be easily apparent from traditional 2D graphs. This can lead to deeper insights into the economic conditions of cities and inform decision making to improve their prosperity.

4 Results and Discussion:

Four unique input variables, including GDP, employment rate, education, and quality of life, were used in our proposed intelligent system; each input variable contains three or four possible linguistic values. The single output generated by our proposed system represents the prosperity of a smart city. To make rule base in fuzzy logic, considering GDP, employment rate, education, and quality of life indicators, which clearly defines the relationship between these indicators and the prosperity of a city. Some of the rules that could be included in the rule base are given below:

- If GDP is high and employment rate is high, then prosperity is high. This rule reflects the idea that a city with a strong economy and high employment is likely to be prosperous.
- If education level is high and quality of life is high, then prosperity is high. This rule reflects the idea that a city with a well-educated population and a high quality of life is likely to be prosperous.
- If GDP is low and employment rate is low, then prosperity is low. This rule reflects the idea that a city with a weak economy and high unemployment is unlikely to be prosperous.
- If education level is low and quality of life is low, then prosperity is low. This rule reflects the idea that a city with a poorly educated population and a low quality of life is unlikely to be prosperous.

These rules can be combined and refined as necessary to produce an accurate and reliable image of the prosperity of a city. The use of fuzzy logic allows for the consideration of the interdependence of the indicators and the possibility of trade-offs between them, leading to a more complete and nuanced depiction of the prosperity of a city. By using fuzzy logic to determine prosperity, researchers and policy makers can account for the uncertainty and complexity of the data and make more informed decisions. For example, they can consider the interplay between the different indicators and make trade-offs between them to optimize the overall prosperity of a city. The ability to account for uncertainty and interdependence of the indicators, as well as the flexibility to incorporate new data and refine the system over time, makes a fuzzy logic-based approach a powerful tool for smart city policymaking.

5 Conclusions:

Smart city policymaking can be a challenging task due to the complexity of the issues involved. There are many factors that contribute to the prosperity of a city, including economic growth, quality of life, environmental sustainability, social equality, and technological innovation. Balancing these competing demands and developing effective policies to support the development of smart cities requires a comprehensive and multidisciplinary approach. AI can play an important role in smart city policymaking by providing decision-makers with valuable insights and analysis to inform their policy choices. As a result, we suggested an intelligent system based on fuzzy logic in this study to assess the success of smart cities. We used four different input variables—GDP, employment, quality of life, and education—for this goal, and our suggested approach produced the prosperity of the city as an output based on these variables, researchers and policymakers may gain a thorough understanding of a city's economic circumstances and then use that information to make defensible decisions to increase its prosperity.

6 Future Works:

The future work for "Developing a fuzzy logic-based approach to Determine prosperity for Smart City Policymaking" may involve a number of different directions, including:

- **Refining the fuzzy logic model:** The authors may wish to further refine the fuzzy logic model they have proposed, taking into account additional indicators of prosperity or incorporating new data sources.
- **Expanding the case studies:** The authors may choose to conduct additional case studies in different cities or regions to validate the efficacy of the fuzzy logic model in a wider range of contexts.
- **Incorporating additional factors:** The authors may choose to incorporate additional factors that contribute to prosperity in the model, such as environmental sustainability, social equality, and technological innovation.
- **Integrating with other decision making tools:** we may choose to integrate the fuzzy logic model with other decision-making tools, such as machine learning algorithms or optimization algorithms, to enhance its overall effectiveness.

These are some examples of the future work that the authors may consider in their research on fuzzy logic-based approach to determining prosperity for smart city policymaking.

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