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Evaluation of Planet Factors of Smart City through Multi-layer Fuzzy Logic (MFL)☆

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Abstract

Internet of Things (IoT) approach is empowering smart city creativities all over the world. There is no specific tool or criteria for the evaluation of the services offered by the smart city. In this paper, a new Multilayer Fuzzy Inference System (MFIS) is proposed for the assessment of the Planet Factors of smart city (PFSC). The PFSC system is categorized into two levels. The proposed MFIS based expert system can categories the evaluation level of planet factors of the smart city into low, satisfied, or good.

1 Introduction

Internet of Things (IoT) is the most frequently discussed worldview that imagines in the future in which all of the things that are used in the daily routine of life must be embedded with microcontrollers, sensors and transceivers for digital transmission and communication, and appropriate protocol nodes. That kind of protocol can be used to make them able to create a great opportunity to speak with each other and with the clients, becoming a vital portion of the Internet [1].

However, such a varied field of the utility of IoT for the smart city makes not only the recognition of best solutions but also a necessity of all related utility situations an alarming challenge. [2]. The most important thing is IoT platform design and development which requires a perfect solution that is called middleware-level solution to enable the seamless interoperability between machine-to-machine based application and existing internet-based service [3].

All the more, by and large, we could state that a smart city procedure goes for utilizing the technology to expand the personal satisfaction in urban space, both enhancing the environmental quality and conveying better administrations to the residents [4].Transmission and information technology are among the most important aspects used to support and change urban city to smart city [5]; therefore, a digital city is frequently utilized synonymous and identical to a smart city. The application and architecture of the IoT paradigm to the smart city is principally alluring to nearby and regional organizations that may turn into the early adopters of such advances. Accordingly, going about as catalyzers for the appropriation of the IoT worldview on a more extensive scale [6].

The purpose of this explanation is to talk about

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a general reference structure for the plan of an urban IoT. Smart city defines the exact features and properties of the urban city.

2 Literature Review

The Internet of Things (IoT) is the interconnection of various physical gadgets, vehicles, mobile, and different things implanted with hardware, programming, sensors, actuators, and availability which empowers these items to interface and trade information [7].

The first important factor for the smart city is sustainable energy integration and consumption for an essential multi-axial complex of smart city design and architecture [8]. The aggressive growth of urban city causes an increase in pollution and waste management matters in most of the countries all over the world [9]. For instance, Pakistan has similarity issues since last few decades even in developed cities including Karachi, Islamabad, and Lahore. Smart city initiatives are aimed to create digital innovation to make the lives of citizens batter and improve urban living sustainably by excelling in environment and properties, transportation and people amenities, such as education, healthcare, and living [10]. To calculate the evaluation of PFSC, we need to follow a specific model similar to swarm intelligence that is advance research in which we have to analyse and identify correspondence algorithms that represent the behaviors modeling techniques. By using swarm Intelligence, we can define many algorithms that represent the behaviors of the swarm of flies and other organisms such as fishes, bees or insects. When we have many inputs and outputs, we have to use MIMO (Multiple-Input and Multiple Outputs) technologies to improve our quality of the system in IoT and smart city [11].

Whereas in PFSC, many other elements are involved, but there is a great role of RFID technology of novelty for traffic blocking and controlling. Sensors play an important role for this purpose that identifies every action by using an RFID reader. At this stage, we have to use an intelligent system to maintain the dynamic changes of time whenever a single action occurs [12].In the current era, new cities have issues about the urbanization, and other improve life standard. The latest research says that social networking requires a specific and precise framework that can help to analyze the data set of social networking sites and sensor devices in the smart city [13].

We need a specific method in which we have to transmit a path that identifies in different devices. A multicarrier method that is Multi-Carrier Code Division Multiple Access (MC-CDMA) provide the solution to this problem [14]. Another important issue is how much Multiple Input and Multiple Output (MIMO) systems are helpful in PFSC. This issue is much highlighted in wireless technologies. MC-CDMA with Alamouti's Space-Time Block Codes (STBC) is the paramount solution of this issue [15]. Fuzzy Logical Controller (FLC) that can be implemented for prototyping panel and mathematical results of PFSC calculations are assessed for altered configuration and input parameters [16].

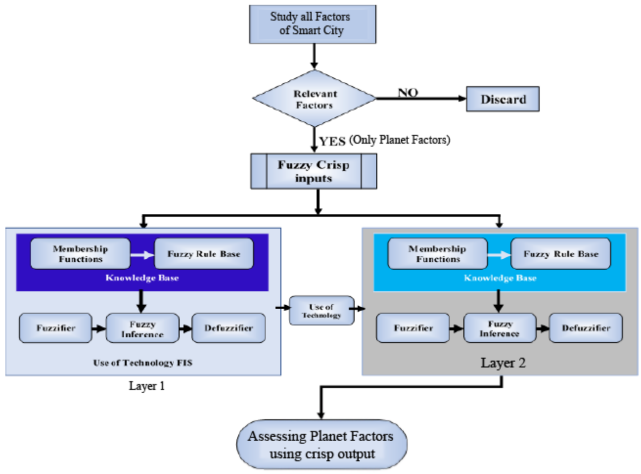


Figure 1. DFD of Proposed Methodology of PFSC

3 Proposed Methodology Multilayer Fuzzy Logic of PFSC System

New processing strategies give fluffy rationale can be utilized as a part of the improvement of insightful frameworks for basic leadership, ID, design acknowledgment, streamlining, and control [17]. Fuzzy surmising guidelines will be an aid for giving a round check to all components in urban areas. The plan is required to encourage wellbeing, economic framework, biological system, and energy and water utilization other parental figures to make choices wisely. In this manner, the IoT based framework can be utilized all the more proficiently without trading off with the nature of the administration of the framework [18]. Figure 1 demonstrates DFD of proposed methodology of PFSC and Figure 2 demonstrates proposed methodology multilayer fuzzy interface system of PFSC.

3.1 Inputs Variables

The membership function of this system gives curve output values between 0 and 1 and also provides a mathematical function that offers statistical values of input and output variables. The only first layer (energy and mitigation factors) considered as level 1, the rest of the layers is correspondence.

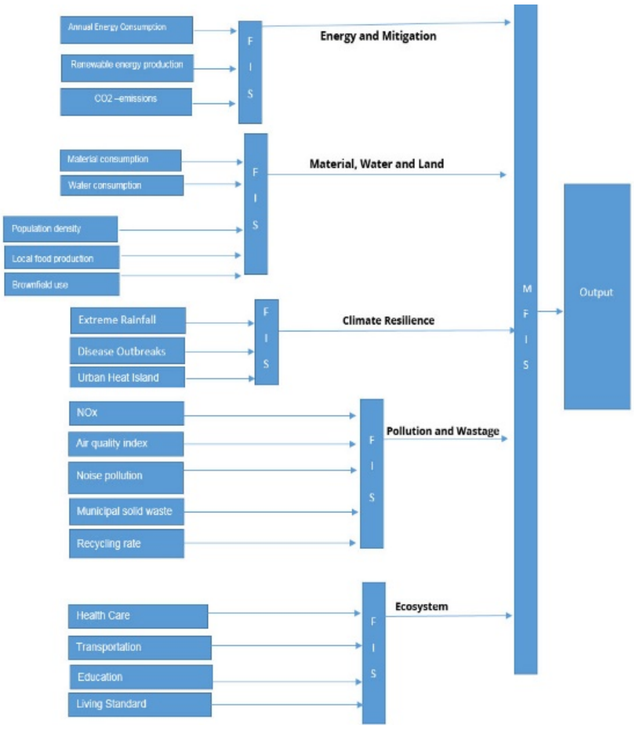


Figure 2. Proposed Methodology Multilayer Fuzzy Interface System of PFSC

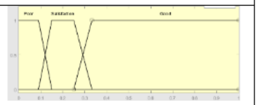
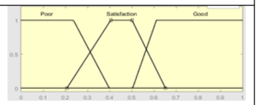
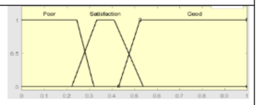
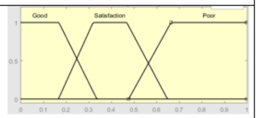
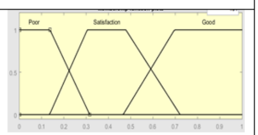
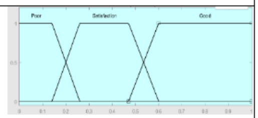
Input/output	Membership Function	Graphical Representation of MF
$EM = E\mu_E(e)$	$\mu_{E,P}(e) = \{\max(\min(1, \frac{0.15-e}{0.1}), 0)\}$ $\mu_{E,SG}(e) = \{\max(\min(\frac{e-0.09}{0.1}, 1, \frac{0.3-e}{0.1}), 0)\}$ $\mu_{E,G}(e) = \{\max(\min(\frac{e-1}{0.1}, 1), 0)\}$	
$MWL = M\mu_M(m$	$\mu_{M,P}(M) = \{\max(\min(1, \frac{0.4-m}{0.1}), 0)\}$ $\mu_{M,SG}(M) = \{\max(\min(\frac{m-0.3}{0.1}, 1, \frac{0.6-m}{0.1}), 0)\}$ $\mu_{M,G}(M) = \{\max(\min(\frac{m-1}{0.1}, 1), 0)\}$	
$CR = C\mu_C(c)$	$\mu_{C,P}(C) = \{\max(\min(1, \frac{0.3-c}{0.1}), 0)\}$ $\mu_{C,SG}(C) = \{\max(\min(\frac{c-0.25}{0.1}, 1, \frac{0.55-c}{0.1}), 0)\}$ $\mu_{C,G}(C) = \{\max(\min(\frac{c-0.42}{0.1}, 1), 0)\}$	
$PW = A\mu_A(a)$	$\mu_{A,P}(A) = \{\max(\min(1, \frac{0.38-a}{0.1}), 0)\}$ $\mu_{C,SG}(A) = \{\max(\min(\frac{a-0.19}{0.1}, 1, \frac{0.68-a}{0.1}), 0)\}$ $\mu_{C,G}(A) = \{\max(\min(\frac{a-0.49}{0.1}, 1), 0)\}$	
$ES = E\mu_{E1}(e1$	$\mu_{E,P}(E1) = \{\max(\min(1, \frac{0.36-e1}{0.1}), 0)\}$ $\mu_{E,SG}(E1) = \{\max(\min(\frac{e1-0.12}{0.1}, 1, \frac{0.72-e1}{0.1}), 0)$ $\mu_{E,G}(E1) = \{\max(\min(\frac{e1-0.49}{0.1}, 1), 0)\}$	
$O = O\mu_O(o)$	$\mu_{E,P}(O) = \{\max(\min(1, \frac{0.09-O}{0.1}), 0)\}$ $\mu_{E,SG}(O) = \{\max(\min(\frac{O-0.14}{0.1}, 1, \frac{0.6-O}{0.1}), 0)\}$ $\mu_{E,G}(O) = \{\max(\min(\frac{O-0.49}{0.1}, 1), 0)\}$	

Figure 3. EMF for Layer One and Layer Two Input/Output Variables Membership Functions Proposed Methodology PFSC System

3.2 Outputs Variables

The output variables for multiple-layer of proposed PFSC needs to be set up. First of all, we have to evaluate the results from layer one; if the results are satisfying the condition, then layer two will be activated.

3.3 Member Function

Membership function represents the curve values ranged between 0 and 1. It is a mathematical notation of input and output variables. FIS input/output variables of EMF for layer one and layer two with a graphical and mathematical representation of the proposed methodology PFSC system is demonstrated in Figure 3; where first five rows represent the input member function while row six represents the output member function.

3.4 Fuzzy Set Operations

The most important set operations in fuzzy are an intersection, union and additive compliment. They manage the essence of fuzzy logic. If there are two fuzzy sets A and B defined on the universe X, x∈X Then the fuzzy set operation can be written as:

$$Intersection(AND) = \mu_{A \cap B}(x) = min(\mu_A(x), \mu_B(x))$$

$$Union(OR) = \mu_{A \cup B}(x) = max(\mu_A(x), \mu_B(x))$$

$$AdditiveComplement(NOT) = \mu_A(x) = 1 - \mu_B(x)$$

3.5 Fuzzy Propositions

A proposition is a statement that is either true or false. There is multi-layered architecture proposed to evaluate PFSC in two levels of layers.

3.5.1 Layer Level One

Here, layer one contains 5-factor layers correspondence with EMF, MWL, CR, PW, and ES. Every layer has its member function represented by variables.

$$EMF = t : A \times R \times C \implies T_1$$

All input and output variable values are mapped from real range to probability ranges because fuzzy expert system works on probability (range 0-1). T-norm function of layer level one can be written as:

$$EMF = t : [0,1] \times [0,1] \times [0,1] \implies T_1$$

Equation 1 and 2 convert the membership functions of fuzzy sets of simulation, Energy and Mitigation (EM), Material, Water and Land (MWL), Climate Resilience (CR), Pollution and Wastage (PW), Echo System (ES) as layer level one.

$$t[\mu_A(a), \mu_R(r)\mu_C(c)] = min(\mu_A(a), \mu_R(r), \mu_C(c)) \quad (1)$$

$$\mu_{A\cap R\cap C}(a,b,c) = t[\mu_A(a), \mu_R(r), \mu_C(c)] \quad (2)$$

$$\mu_{H\cap T\cap E}(h,t,e) = t[\mu_H(h), \mu_T(t), \mu_E(e)] \quad (3)$$

$$\mu_{A\cap R\cap C}(a,r,c) = min(\mu_A(a), \mu_R(r), \mu_C(c)) \quad (4)$$

$$\begin{gathered}\mu_{M\cap W\cap P\cap L}(m,w,p,l) = \\ min(\mu_M(m), \mu_W(w), \mu_P(p), \mu_L(l))\end{gathered} \quad (5)$$

Equation 4 and 5 represent the minimum of the intersection of all sets.

3.5.2 Layer Level Two

Layer two contains five member functions respectively EM, MWL, CR, PW, and ES. Every layer has their member function represented by variables.

$$\begin{gathered} t : EM \times MWL \times CR \times PW \times ES \implies Lt \\ t : [0,1] \times [0,1] \times [0,1] \times [0,1] \times [0,1] \implies Lt \\ t[\mu_{EM}(em), \mu_{MWL}(mwl), \\ \mu_{CR}(cr), \mu_{PW}(pw), \mu_{ES}(es)] \\ = min(\mu_{EM}(em), \mu_{MWL}(mwl), \\ \mu_{CR}(cr), \mu_{PW}(pw), \mu_{ES}(es))] \\ \mu_{EM\cap MWL\cap CR\cap PW\cap ES} \\ (em, mwl, cr, pw, es) = \\ min(\mu_{EM}(em), \mu_{MWL}(mwl), \\ \mu_{CR}(cr), \mu_{PW}(pw), \mu_{ES}(es)) \end{gathered} \quad (6)$$

Equation 6 specifies the minimum of the intersection of all sets.

3.6 Lookup Table

The fuzzy rule base is the important element of Fuzzy Inference System (FIS) because other components of FIS like rules surface and rules viewer are dependent upon fuzzy rule base. Fuzzy rule base of proposed PFSC contains 27 rules at layer one (Only for EMF) and denoted by R_{α^n}, where $1 \leq n \leq 27$.

R_{α^3} = IF ES is Poor AND PW is Poor AND CR is Satisfied AND MWL is Poor AND EM is Poor that represents weightage of PFSC is very poor.

$$\begin{gathered}\mu_{p1}(em, mwl, cr, pw, es) = \mu_{Poor}(ES), \\ \mu_{Poor}(PW), \mu_{Sat}(CR), \mu_{Good}(MWL), \mu_{Poor}(EM)\end{gathered}$$

$R_{\alpha^{300}}$ = IF CR is Satisfaction AND MWL is Good AND EM is Good that represents weightage of PFSC is very Good.

$$\begin{gathered}\mu_{G1}(em, mwl, cr, pw, es) = \\ \mu_{n/a}(ES), \mu_{n/a}(PW), \mu_{Sat}(CR), \\ \mu_{Good}(MWL), \mu_{Good}(EM)\end{gathered}$$

$$\begin{gathered}\mu_{SCPF}(p1, s1, g1) = \\ max(min(1, \frac{0.09-0}{0.1}), 0)| \\ max(min(\frac{0-0.14}{0.1}, \frac{0.06-0}{0.1}), 0)| \\ max(min(\frac{0-0.49}{0.1}, 1), 0)\end{gathered}$$

Fuzzy rule PFSC System (Layer Two) contains 300 rules denoted by R_{α^n}, where $1 \leq n \leq 300$.

3.7 Mamdani Implications

The fuzzy IF-THEN rules R_{α^27}, $R_{\beta^1 44}$, $R_{\gamma^2 7}$, $R_{\pi^1 20}$, and $R_{\phi^2 7}$ are with membership functions of the first level layer as follow:

$$R_{\alpha^n} = \mu_{EMF(a,r,c)}$$

A1 = if use of a,r,c are poor condition
Then the fuzzy output must be
A2 = use of Energy and Mitigation Factors (EMF) must be poor for first level layer

$$\mu_{A1}(a,r,c) = \mu_{poor}(a)\mu_{poor}(r)\mu_{poor}(c)$$

or we can write it as:

$$\mu_{A1}(a,r,c) = \left\{ \begin{matrix} (\frac{1000-a}{0.1})(\frac{900-r}{0.1})(\frac{09-c}{0.1}) \\ 0 \end{matrix} \right\}$$

or

$$\left\{ \begin{matrix} \frac{(1000-a)(900-r)(09-c)}{(0.1)^3} \\ 0 \end{matrix} \right\}$$

The output of fuzzy are as follow:

$$\mu_{A2}(t) = \mu_{Poor}(t)$$

$$\mu_{A2}(t) = \left\{ \begin{matrix} \frac{(0.15-t)}{(0.1)} \\ 0 \end{matrix} \right\}$$

$$ift \implies [0,1]$$

Similarly, we can get rest of layer $R_{\alpha^{140}}$, $R_{\beta^{27}}$, $R_{\gamma^{120}}$, and $R_{\pi^{27}}$.

$R_{\beta 1^{3}00}$ for the second level layer with membership functions are written as

$$R_{\beta 1^{3}00} = \mu_{SCPF}(em, mwl, cr, pw, es))$$

Suppose:

B1 = IF ES is Poor AND PW is Good, AND
CR is Poor AND MWL is Poor AND EM is Poor,
Then fuzzy output must be
B2 = weight of PFSC is very poor
Then we may calculate the fuzzy product of
simulation:

$$\mu_{SCPF}(em, mwl, cr, pw, es) = \mu_{poor}(ES), \mu_{poor}(MWL), \mu_{poor}(CR), \mu_{poor}(PW), \mu_{poor}(EM)$$

or we can write it as

$$\mu_{B1}(em, mwl, cr, pw, es) = \left\{ \begin{matrix} (\frac{(0.15-es)}{(0.1)})(\frac{(0.4-mwl)}{(0.1)})(\frac{(0.3-cr)}{(0.1)})(\frac{(0.38-pw)}{(0.1)})(\frac{(0.36-em)}{(0.1)}) \\ 0 \end{matrix} \right\}$$

$$= \left\{ \begin{matrix} (\frac{(0.15-es)(0.4-mwl)(0.3-cr)(0.38-pw)(0.36-em)}{(0.1)^5}) \\ 0 \end{matrix} \right\}$$

$$if es, mwl, cr, pw, em \implies [0, 1]$$

The output of fuzzy are:

$$\mu_{B2}(t) = \left\{ \begin{matrix} (\frac{(0.09-t)}{(0.1)}) \\ 0 \end{matrix} \right\}$$

$$if t \implies [0, 1]$$

3.8 Fuzzy Interface Engine

The process of combining the fuzzy IF-THEN rules from the fuzzy rule base into a mapping from a fuzzy input set to fuzzy output based fuzzy logic principle is called the fuzzy inference engine. The main component of fuzzy inference is membership functions, fuzzy logic operators, and if-then rules. All rules in the fuzzy rule base are combined into a single fuzzy relation that lies under the inner product on input universes of discourse, which is then viewed as a single fuzzy IF-THEN rule. A reasonable operator for joining the rules is union.
Layer one IF-THEN fuzzy represent as:

$$R_{\alpha^n} = A^n \times R^n \times C^n$$
$$\mu_{A \cap R \cap C}(a, r, c) = \mu_A(a) \cap \mu_R(r) \cap \mu_C(c) \tag{7}$$

Interpreted as a single fuzzy relation defined by:

$$R_{27} = \sqcup_{n=1}^{2} 7 R_a^n$$

Suppose π, λ, and ψ be any three arbitrary fuzzy sets and are also input and output to the fuzzy inference engine, respectively. To view R^{27} as a single fuzzy IF-THEN rule and using the generalized modus ponens:

$$\mu_{Poor \cap Satf \cap Accept}(\varphi) = Sup_{\lambda \epsilon (A,R,C)}$$
$$t[\mu_\lambda(A, R, C), \mu_{R_{27}}(A, R, C)]$$

Using product inference engine format we have:

$$\mu_\varphi(T) = max_{0 \leqslant x \leqslant 27}[Sup_{a,r,c} \epsilon U(\mu_{A,R,C}(a, r, c))$$
$$(\Pi_{k=1}^{27}(\mu_{a_k, r_k, c_k(a_k}, r_k, c_k))\mu_\varphi x(T))]$$

Layer Two IF-THEN fuzzy represent as:

$$R_\beta n = E^n \times M^n \times C^n \times P^n \times EM^n$$
$$\mu_{E \cap M \cap C \cap P \cap EM}(e, m, c, p, em) =$$
$$\mu_E(e) \cap \mu_M(m) \cap \mu_C(c) \cap \mu_P(p) \cap \mu_{EM}(em)$$

Interpreted as a single fuzzy relation for layer two is defined by:

$$R_{300} = \sqcup_{n=1}^{300} R_a^n$$

Interpreted as a single fuzzy relation defined as:

$$R_{a^n}$$

3.9 De-Fuzzifier

For discrete membership function, the defuzzified value denoted as x^* using COG is defined as:

$$x^* = \frac{\sum_{i=1}^{n} x_i \mu(x_i)}{\sum_{i=1}^{n} \mu(x_i)}$$

where x_i indicates the sample element, $\mu(x_i)$ is the membership function, and n represents the number of elements in the sample. The center of gravity defuzzifier specifies x^* and x^{**}, as the center of area covered by a member function of A and B.
Center of Gravity (COG) for layer one and two are computed as represented in equation 8 and 9, respectively.

$$x^* = \frac{\int \Lambda \mu_a(\Lambda) d\Lambda}{\int \mu_a(\Lambda) d\Lambda} \tag{8}$$

$$Center of gravity (COG) for Layer 2$$

$$x^* = \frac{\int B \mu_b(B) dB}{\int \mu_b(B) dB} \tag{9}$$

Where $\int$ is the conventional integral.

Figure 4 represents the 3D view of rule surface of proposed PFSC only based on CR and EM. It observed that PFSC weightage is Good (Yellow shade) if CR is $\geq$0.6 (60%), and PFSC weightage is Satisfy (Greenish Shade) when EM Simulation is lain between 0.15 and 0.4 (15% and 40%). Otherwise, PFSC weightage is Weak or Poor (Bluish Shade).

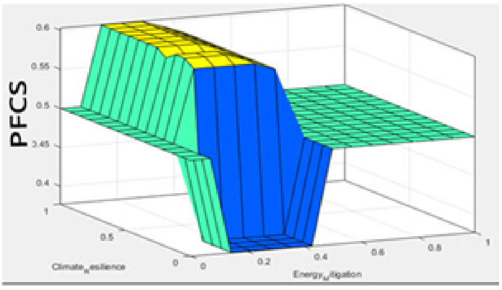


Figure 4. Rule Surface of Proposed PFSC based on Climate Resilience and Energy Factors

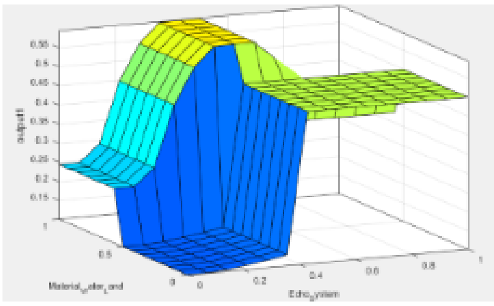


Figure 5. Rule Surface of Proposed PFSC System Based on MWL and ES

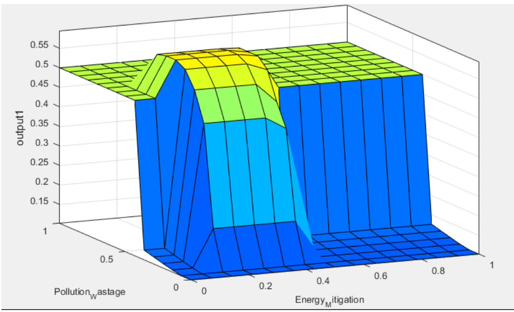


Figure 6. Rule Surface of Proposed PFSC System Based on PW and MWL

Figure 5 and Figure 6 represent the 3D view by prevailing different input parameter values. The former is based on MWL and ES, while the latter is based on PW and MWL. Yellow, Greenish, and Bluish shade represents weightage Strong, Good, and Poor respectively.

4 Simulation Results

For layer two simulation results, the five-member function has 300 inputs and outputs representing layer-2's, and results show that what weight is for PFSC. Since layer two evaluation is final, it indicates the actual strength and feasible planet factors for the smart city. Figure 7 shows that if the values ES, EMF, and CR are in a lower range while PW and MWL are in a high range, then PFSC is not an efficient condition. Figure 8 shows that if the values ES and EMF are not available while CR is in an

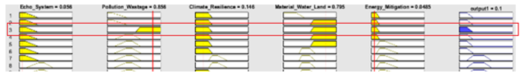


Figure 7. Layer Two Lookup Diagram for Proposed PFSC System (Poor)

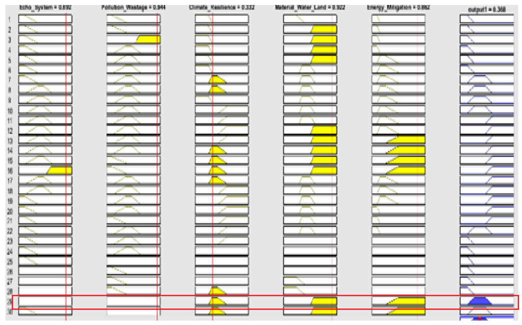


Figure 8. Layer Two Lookup Diagram for Proposed PFSC System (Satisfy)

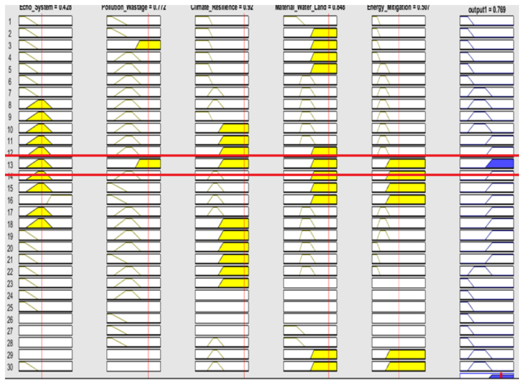


Figure 9. Layer Two Lookup Diagram of Proposed PFSC System (Good)

average range, PW and MWL are in a high range, then PFSC is an efficient condition. Figure 9 shows that if the values ES and EMF are not available while CR is in an average range, PW and MWL are in a high range, then PFSC is an efficient condition.

5 Conclusion

The connected approach for computing smart indicator loads features, for choosing such criteria, with the significance of the decision maker's subjectivity. Indeed, doling out the heaviness of a savvy pointer regarding another smart marker for planet factors, each decision maker is conveyed to reason in a less target way [19]. If there should arise an occurrence of a real city, the foundation of right qualities requires the master's commitment to the different picked fields [20]. This research has opened doors of innovation for different major projects in Pakistan. Gwadar is Pakistan's biggest up-coming project, started a few years ago. Although the first phase of the Gwadar port has been established, and billions of dollars have been invested in infrastructure, yet there is no evaluation and estimation weight for supporting and validity for a smart city. By using this model, we can get a good estimation of the evaluation of this city for the PFCS system. Consequently, it will be conceivable to furnish the arrangement creator with data for "ready consultation" to give him the data that permit to visit and to gauge the impacts of his mediation. The proposed creative framework results in an undeniably expanded understanding and essential use, for both the chiefs and the resident, without respecting abilities and individual subjectivity.

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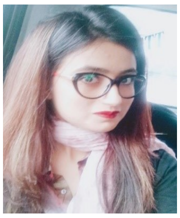

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