

A Fuzzy Approach for an IoT-based Automated Employee Performance Appraisal

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Abstract: The ubiquitous Internet of Things (IoT) through RFIDs, GPS, NFC and other wireless devices is capable of sensing the activities being carried around Industrial environment so as to automate industrial processes. In almost every industry, employee performance appraisal is done manually which may lead to favoritisms. This paper proposes a framework to perform automatic employee performance appraisal based on data sensed from IoT. The framework classifies raw IoT data into three activities (Positive, Negative, Neutral), co-locates employee and activity in order to calculate employee implication and then performs cognitive decision making using fuzzy logic. From the experiments carried out it is observed that automatic system has improved performance of employees. Also, the impact of the proposed system leads to motivation among employees. The simulation results show how fuzzy approach can be exploited to reward or penalize employees based on their performance.

Keywords: Employee Performance appraisal, fuzzy logic, internet of things (IoT), cognitive decision making.

1 Introduction

Internet of things (IoT) is a dynamic worldwide mesh where physical and virtual assets having unique identification perform interoperability functions through sensors, RFIDs (Radio Frequency Identifiers), GPS, NFC (Near Field Communication), actuators and other wireless devices. IoT has capabilities to build a powerful Industrial system; therefore, it transpires a new term 'Smart Industry'.

Although, IoT has lead to huge advancements in Industrial processes but still some industries manually appraise performance of their employees. A manual employee performance appraisal system is prone to fallacy and intentional or unintentional discrimination among employees. A research carried out by Intartaglio revealed that only 36% of Industrial employees are pleased with manual performance appraisal [Intartaglio (2000)]. In such a system, employees are supervised only by their superiors for their current performance, while disregarding any poor performance in early appraisal period. According to Strauss [Strauss (1958)] employee reviewing should be a continuous process. An excellent performance renders employees bonus while penalizing the delinquent employees. Thus, Industry takes decision just on the basis of decisions made by supervisors. Such decisions can be discriminatory and unjustified and can lead to dissatisfaction,

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discouragement among employees. So, by considering aforementioned facts, this paper proposes an automated employee performance appraisal system that continuously monitors employee's behavior and activities by leveraging IoT with an integration of fuzzy logic to reward the best performer in industry.

2 Literature survey

The Accumulate and Ubiquitous IoT can be leveraged in various industrial domains to offer smart solutions. Due to this, IoT has rapid vogue in Industrial processes. Da Xu, He, Li (2014), Kaliczyńska and Dąbek (2015) highlights the significance of Industrial IoT. IoT has been leveraged in various applications such as packing and printing manufacturing [Li, Pi, Han, Ran, Chen and Ke (2016)], car manufacturing [Khaleel, Conzon, Kasinathan, Brizzi, Pastrone, Pramudianto, Eisenhauer, Cultrona, Rusina, Lukac and Paralic (2015)], Quality control [Ondemir and Gupta (2014)], safety in coal Mines [Kunkun and Xiangong (2014)] and other.

Data through IoT devices (sensors, RFIDs, GPS etc.) are sensed from the industrial surroundings. The sensed data need to be processed to form information. This conversion from data to information is done by data mining techniques. Tsai et al. [Tsai, Lai, Chiang and Yang (2014)] addressed mining techniques for internet of things. Kim et al. [Kim, Lee, Ryo and Kim (2014)] proposed a framework for mining spatial co-location patterns. Rashidi et al. [Rashidi, Cook, Holder and Edgecombe (2011)] gave a proposal to track and monitor daily activities in smart environment. The information so formed needs to be evaluated in order to make decisions. According to Wu et al. [Wu, Ding, Xu, Feng, Du, Wang and Long (2014)], a cognitive IoT is the one in which data acquired by IoT devices is involved in cognitive decision making. There are various decision making processes such as agent based model [Schlesinger and Parisi (2001)], Bayesian decision model [Lee, Yang and Cho (2015)], neural networks [Mese and Torrey (2002)], game theory [Cristóba (2014)], and Fuzzy logic [Aló Korvin and Modave (2002)] [Arshad, Islam and Khaliq(2014)]. Authors in [Aló Korvin and Modave (2002)] [Arshad, Islam and Khaliq (2014)] [Wu, Ding, Xu, Feng, Du, Wang and Long (2014)] deployed fuzzy logic to make optimal decision and performance appraisals in industry.

Table 6 compares various decision making models. Among these models, fuzzy logic has the lowest computation time and is simple. The structure of artificial neural networks is complex; it may give a non-deterministic outcome, so is less accurate. On the other hand, Bayesian decision making models have a convoluted design; it results into either occurrence or non-occurrence of an event. Game theory decision model cannot be analyzed for all competitive problems. It is considered an unrealistic/impractical approach since one player has knowledge of other player's pay-off matrix. Compared to these decision models, fuzzy logic is highly accurate as it yields to an outcome in between yes (1) or no (0).

Table 1: Comparison of decision making models

Attributes Decision Making Models	Computation Time	Complexity	Accuracy in Outcome
Artificial Neural Networks	High	Complex	Least Accurate (May Give Non-Deterministic Output).
Bayesian Decision Making	High	Highly Complex	Less Accurate (Gives Output as Yes or No).
Game Theory	High	Complex Pay-Off Matrix	Accurate (Is an Un-Realistic Approach).
Fuzzy Logic	Low	Simple	Highly Accurate (Gives Output In between Yes or No).

3 Proposed framework and methodology

Figure 1. demonstrates the workflow of an automated employee performance appraisal system. This system comprises of 3 sections:

- (1) Internet of Things Section.
- (2) Data Processing Section.
- (3) Decision Making section.

Data Regarding industrial surroundings and Employee is collected via IoT devices. The collected data is then transformed by Data processing section into knowledge. The Knowledge so obtained is then analyzed to take decisions regarding employee performance using fuzzy logic approach. The detailed explanation of the system is as follows:

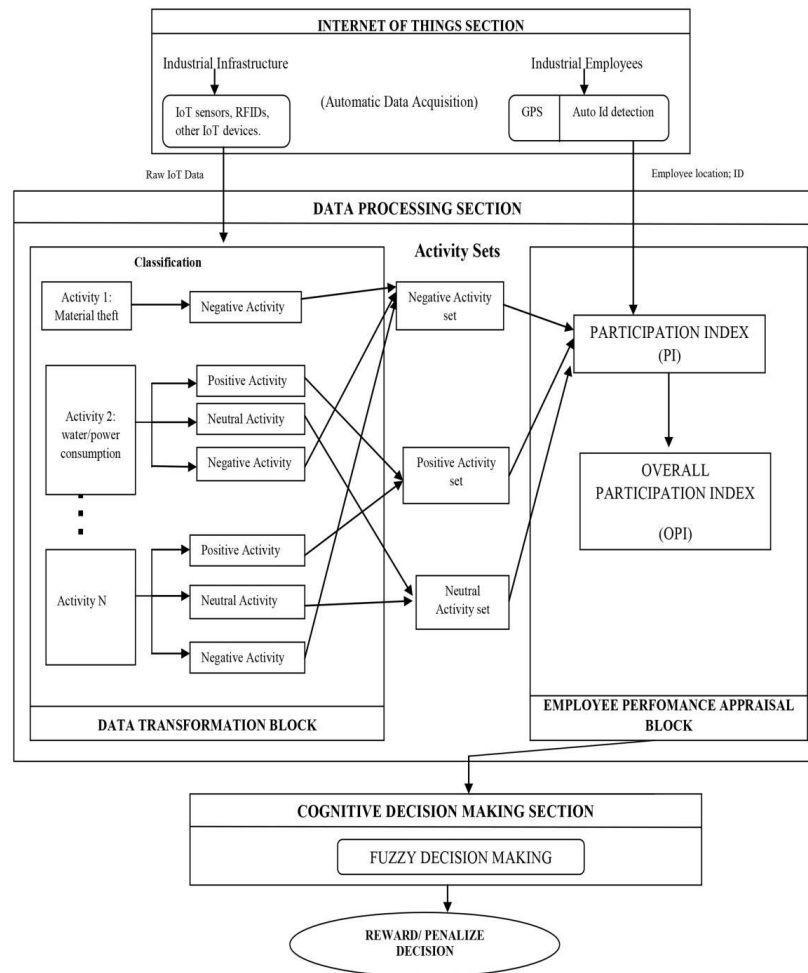


Figure 1: Proposed industrial employee performance appraisal system

3.1 Internet of things section

IoT devices installed in industrial infrastructure acquire data from the surroundings. The acquired data can be humidity monitoring, material theft, power consumption etc. For such acquisition thermostats, sensors embedded with RFIDs, and other sensors are deployed. This section also attains the location of employees from GPS as well as automatically detects employee ID. Table 2 displays various IoT devices that are needed for detecting employee activities.

3.2 Data processing section

3.2.1 Data transformation block

This block collects data sensed by IoT devices, compares it with previous data and classifies it into 3 activity sets: Positive, Negative, and Neutral.

Table 2: IOT devices required for various employee activities.

S. NO.	Employee Activity	IOT Device (Detection System)
1.	Product Identification/ Material Theft	RFIDs
2.	Location	GPS
3.	Attendance	Biometric Attendance
4.	Team Work	Identity Cards With Embedded GPS

Positive Activity set (P_A) is a collection of all activities that are profitable to the industry. For example, accomplishment and sensible usage of water/ electricity are positive activities and together they form positive activity set. Negative Activity set (N_A) is a collection of those activities that results into loss to industry. For example, material theft and information leakage are negative activities and together they form Negative Activity set. Neutral Activity Set (NU_A) is a collection of neutral activities that are neither responsible for any profit nor any loss to the industry but are necessary for proper working of industry. An activity can be positive, negative or neutral. For instance, if water consumption level is high, then it is a negative activity, if it is low, then it is a positive activity, otherwise it is neutral. Table 8 demonstrates activity classification of some industrial activities.

Table 3: Activity classification of some industrial activities

S. NO.	ACTIVITY	POSITIVE	NEGATIVE	NEUTRAL
1	Material Theft		X	
2	Water Consumption	X (Sensible usage)	X (wastage)	X (normal)
3	Power Consumption	X (low)	X (high)	X (normal)
4	Team Work	X (high co-ordination)	X (lack and interest and co-ordination)	
5	Accomplishment	X		

Data transformation Block performs activity classification by first comparing the raw data gathered from IoT devices with the previous data stored in database. If recently fetched value is lower than the previous database value then it is a positive activity and the difference in two values gives profit, however if recently fetched value is higher than previous value then it is a negative activity and the difference in two values gives profit. On the other hand, if values lie close to each other then it is a neutral activity and there is no profit or loss.

$$P_A + N_A + NU_A \rightarrow A$$

Collection of all types (positive, negative, neutral) of Activities form Activity Set (A).

3.2.2 Employee performance appraisal block

Activity set from Data Transmission Block and Employee Location from Internet of Things section are two inputs of employee appraisal block. To execute this block Apache Spark is preferred as it is 100 times faster than Hadoop MapReduce. This block evaluates participation of employee in positive, negative, neutral activities. It is assumed that an employee participates in an activity if both employee and activity are co-located. For this participation Index (PI) [113] is calculated for all activity sets by using the equations:

For positive activity set:

$$PI(P_A, i) = \frac{n^i P_A}{|P_A|}$$

For Negative activity set:

$$PI(N_A, i) = \frac{n^i N_A}{|N_A|}$$

For Neutral activity set:

$$PI(NU_A, i) = \frac{n^i NU_A}{|NU_A|}$$

Participation index ranges from 0 to 1 since $n^i X \leq |X|$ where X can be P_A , N_A or NU_A .

After calculating PI (Participating Index), overall Participation of employee in industrial activities is calculated by

$$OPI(i) = \begin{cases} PI(P_A, i) - PI(N_A, i), & \text{if } PI(NU_A, i) > \phi \\ PI(P_A, i) - PI(N_A, i) - (\phi - PI(NU_A, i)), & \text{otherwise} \end{cases}$$

The value of OPI ranges from 1 to $-(1+\phi)$, value of ϕ is industry dependent.

For calculating this range best and worst case are considered. In the best case employee will shows maximum involvement in positive activities and minimum in negative activities i.e $PI(P_A, i)=1$ and $PI(N_A, i)=0$ and $PI(NU_A, i)> \phi$ because employee in this case will be involved in more neutral activities. So $OPI = (1-0)=1$. On the other hand, in worst case employee will shows maximum involvement in negative activities and minimum in positive activities i.e. $PI(P_A, i)=0$ and $PI(N_A, i)=1$ and $PI(NU_A, i)=0$. So, $OPI = (0-1-(\phi-0)) = -(1+\phi)$.

Table 4: Notations Used

NOTATION	MEANING
P_A	Positive Activity Set
N_A	Negative Activity Set
NU_A	Neutral Activity Set
$ P_A $	Cardinality of P_A
$ N_A $	Cardinality of N_A
$ NU_A $	Cardinality of NU_A
$n^i P_A$	number of positive activities in which i^{th} employee and activity a_p are co-located; where $a_p \in P_A$ and $n^i P_A \leq P_A $

n^iN_A	number of negative activities in which i^{th} employee and activity a_n are co-located; where $a_n \in N_A$ and $n^iN_A \leq N_A $
n^iNU_A	number of neutral activities in which i^{th} employee and activity a_{nu} are co-located; where $a_{nu} \in NU_A$ and $n^iNU_A \leq NU_A $
$PI(P_A, i)$	Participation Index of i^{th} Employee in P_A
$PI(N_A, i)$	Participation Index of i^{th} Employee in N_A
$PI(NU_A, i)$	Participation Index of i^{th} Employee in NU_A
$OPI(i)$	Overall Participation Index of i^{th} Employee

3.3 Decision making section

Decision making section automates industrial decision making process by using Fuzzy logic. This section will be implemented in Matrix Laboratory (MATLAB) platform.

3.3.1 Fuzzy decision making

STEP 1: Define input and output Linguistic variables and their numerical ranges. Input Linguistic variable:

- OPI-the value of OPI ranges from 1 to-(1+ ϕ) Where; value of ϕ is industry dependent.
- Profit/ Loss (range 0-100)

Output Linguistic Variable: DECISION: REWARD and PENALIZE.

STEP 2: Construct membership functions for each linguistic variable

STEP 3: Construct Rule BASE

- If (OPI is high) and (profit is high) and (loss is low) then (decision is reward)
- If (OPI is low) and (profit is low) and (loss is high) then (decision is penalize)
- If (OPI is high) and (profit is low) and (loss is low) then (decision is penalize)
- If (OPI is high) and (profit is low) and (loss is high) then (decision is penalize)
- If (OPI is low) and (profit is low) and (loss is low) then (decision is penalize)

4 Experimental setup and results

4.1 Experimental setup

The experiment is carried out in a mining industry [Chen (2006)]. Flowchart below shows the scenario of mining industry and the activities that are carried out in this industry. The activities are classified into positive, negative and neutral classifications. The experiment was conducted by selecting 20 employees from a mining industry.

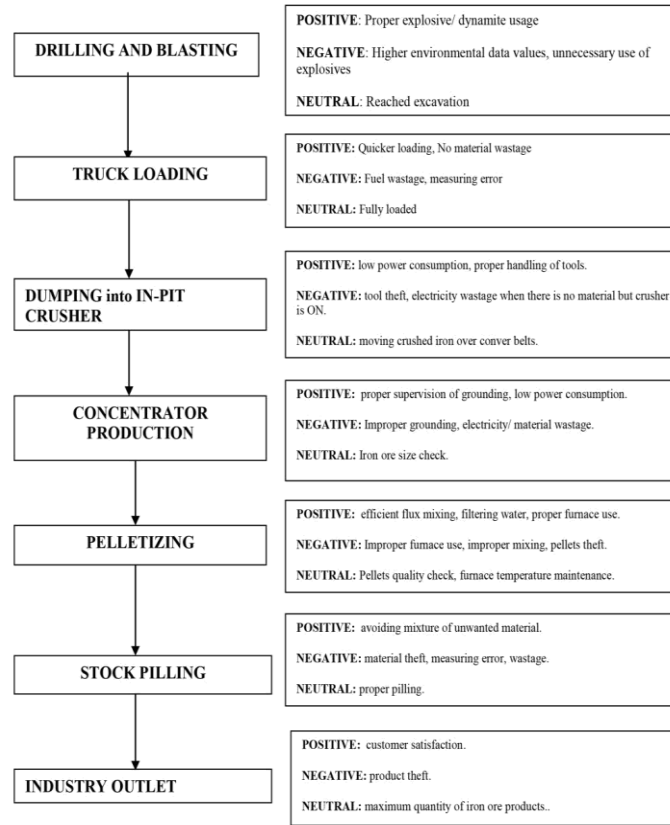


Figure 2: Mining activities carried out in mining Industry.

Table 5 shows the details of those selected employees, each employee is given a unique id.

Table 5: Employees selected for experiment

E_ID	NO. of Employees	Designation
E01-E05	5	Drillers, shot firers
E06-E09	4	Truck drivers
E10-E11	2	Electricians
E12	1	Supervisor
E13-E17	5	Mining Laborers
E18-E20	3	Mining Engineers

The experiment is carried out for three days.

Day 1: The objective of day 1 is to appraise the actual performance of employees and compare it with manual system. This experiment is performed without any notification to employees that they are being monitored this is because employees tend to perform better if they are informed beforehand. At the end of the day some employees are given rewards

while others with low performance are penalized.

Day 2-3: The objective of these two days is to depict the effect of automated system on performance of employee. In this experiment employees are notified that they are being monitored by automated IoT system.

4.2 Results and discussions

Table 5 shows the detailed results acquired for the first three days of experiment. This table shows the values of OPI for each employee computed by the system. Threshold value taken here is 0.5.

Table 5: OPI values calculated by system for day 1-2-3

E_ID	DAY 1	DAY 2	DAY 3
E01	0.15	0.5195	0.5824
E02	0.7267	0.741	0.808
E03	0.4667	0.6146	0.6978
E04	0.25	0.3494	0.4538
E05	0.4	0.697	0.7332
E06	0.2317	0.4637	0.6871
E07	0.4833	0.5589	0.7435
E08	0.3	0.6202	0.6491
E09	0.5667	0.8825	0.9364
E10	0.861	0.88	0.8974
E11	0.0167	0.082	0.1231
E12	0.15	0.1888	0.2342
E13	0.8333	0.85	0.9359
E14	0.1167	0.2658	0.4968
E15	0.3167	0.4502	0.5679
E16	0.65	0.7598	0.7897
E17	0.2	0.4183	0.7578
E18	0.5167	0.789	0.9532
E19	0.1905	0.5346	0.8525
E20	0.6833	0.7807	0.9971

4.2.1 Comparison of manual system with Day 1 results

Table 6 shows the grades awarded to the employees calculated using Table 7. The numeric grading shown in table 6 is taken for comparison purposes because of discrepancy in grading practices followed by proposed and manual system. The manual appraisal system uses

grading A+, A, B+, B and C for appraising employee performance while the proposed fuzzy system gives numerical value (OPI). Hence for comparison of these two systems, grading should be similar.

The manual grade is acquired from the filled performance appraisal forms which are leveraged in manual appraisal system. They are compared with day 1's grade. As stated earlier, employees were not notified about monitoring through IoT systems on this day (day 1), so it depicts their actual performance. The comparison results are shown in Fig 3. It can be noticed from the figure that only three out of twenty employees are having same grade under both the systems. The other employees were either over evaluated or under evaluated.

Table 6: Statistical analysis of automated and manual grades

E_ID	Automated grading	Manual grading
E01	1	3
E02	3	1
E03	2	2
E04	1	4
E05	2	1
E06	1	3
E07	2	4
E08	1	2
E09	3	3
E10	4	1
E11	1	3
E12	1	2
E13	4	1
E14	1	2
E15	1	4
E16	3	1
E17	1	4
E18	2	3
E19	1	3
E20	3	1

Table 7: Grading system

Grading on Number Scale	Manual Grading	Automated Grading
4	A+	0.851-1
3	A	0.51-0.85
2	B+	0.351-0.5
1	B	0-0.35
0	C	-(1+φ)-0

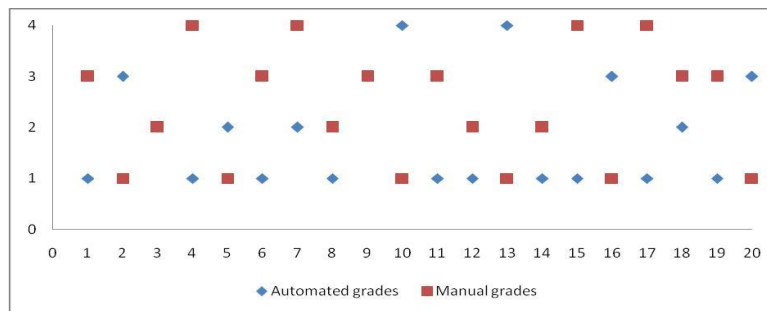


Figure 3: Comparison of grades of day 1 with manual system.

4.2.2 Comparison of results for day 1-2-3

The OPIs of all the employees for first three days of the experiment are shown in Table 5. Figure 4 demonstrates the comparison of performance of employees for day 1-3 on the basis of data shown in Table 5. It can be examined from the results that there is a sudden increase in performance of almost all the employees on day 2. The employees further upgraded their performance on day 3. This demonstrates that employees perform effectively when they are continuously monitored by an automated IoT system.

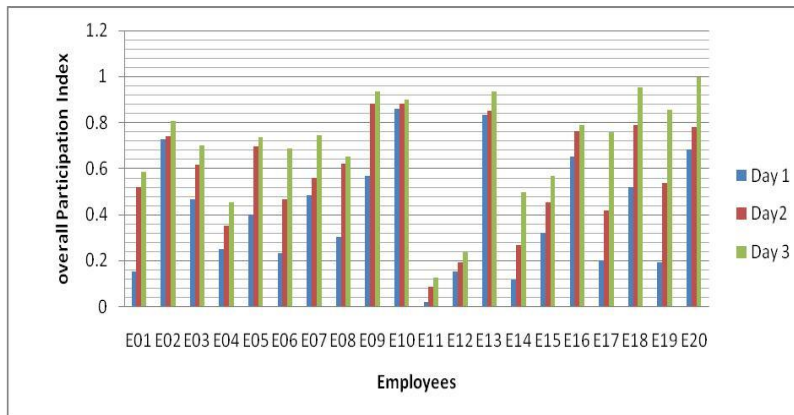


Figure 4: Performance comparison of twenty employees for three days.

4.2.3 Decision making using fuzzy logic approach

The OPI values so obtained can be applied to make reward or penalty decision using fuzzy logic approach. Figure 5 shows the membership values defined for input and output of fuzzy logic system.

Decision Membership functions:

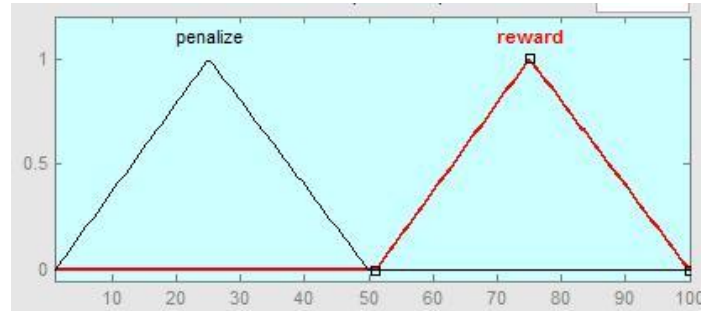


Figure 5: Membership functions for decision

Surface View:

Figure 6 shows the relation between various input (OPI, Profit, Loss) and output (Decision).

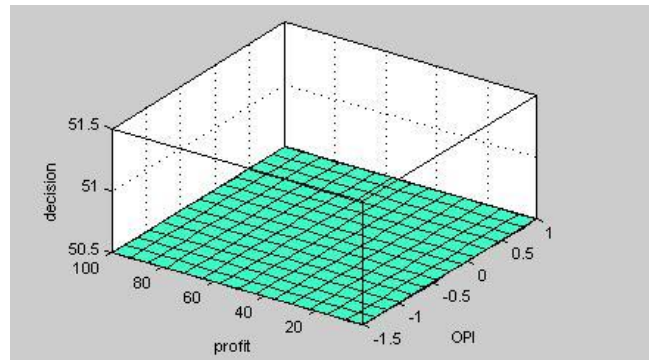


Figure 6: Relation between input and output

4.3 Evaluation of employees performance

The results in figure 7 shows how an employee's performance can be evaluated and decision can be taken regarding reward or penalty. A high OPI value of 0.503, profit of 72 and loss of 18.8 results into a decision= 75.3 which is a high value on the scale of 0-100. So, the employee is rewarded by the industry.

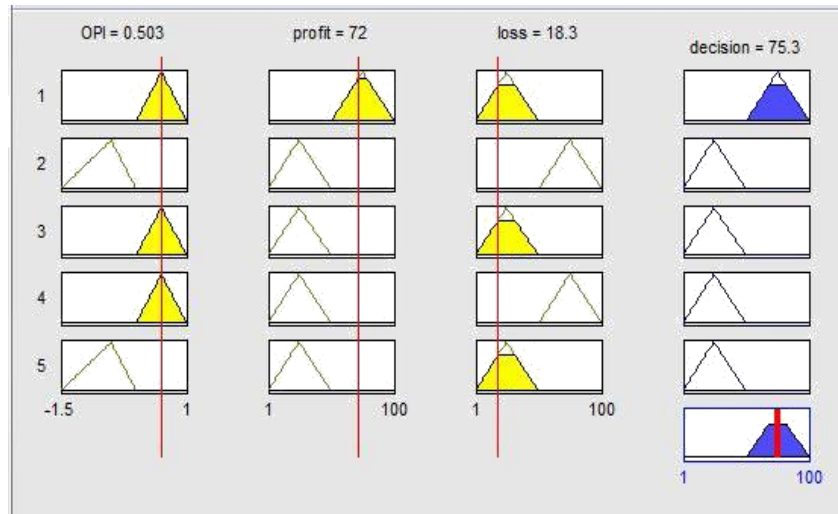


Figure 7: Evaluation of Employees Performance and decision is made on the basis of OPI value, a high OPI value indicates the best performance of employee and considered for reward.

5 Conclusions

By leveraging the proposed framework, Industries will be able to increase employee morale and hence make profit from it. The decision regarding rewarding the best employee is based on the IoT data such as employee's location, accomplishment, Team work etc., processing this data to calculate overall participation Index of employee in association to positive, negative and neutral activity. The index, profit and loss so obtained can be used for making decision using fuzzy logic. Fuzzy logic defines membership values to take accurate decision. The proposed system is capable of eliminating favoritisms, discriminatory, dissatisfaction among employees which in turn is capable of earning profit for industry. Future work can be deployed in various decision making processes of diverse industries such as supply chain, university/School staff evaluation, Mining and any more.

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