AI based Armed Surveillance Robot

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Abstract: This paperwork focuses on robots which perform functions such as Target Firing, Surveillance and Metal Detection. Around the border areas where regular conflicts take place, there is a need for an automated mechanism to take immediate actions in case of invasion from the intruders and to reduce the human loss. In such areas, equipped autonomous robots with AI vision as well manually controlled firing robot helps in monitoring the conditions in border areas.

Keywords: AI vision, OpenCV, Face Detection, Firing, Metal Detection, GSM, GPS, Surveillance.

1. INTRODUCTION

Governments of numerous nations are striving to provide good support for border security. Still, border security continues to account for challenges to governments around the world. Other countries have already started to replace the soldiers with automated robots, the system is necessary for self-defence and other contextual factors. In order to reduce the human loss in the war fields, there is a need to develop an automated system. This paper is based on an AI based armed robot, which performs spying and surveillance and then makes decisions based on real-time conditions. The data received from the surveillance operations are transmitted to the base stations through the Wi-Fi signal and any anomaly detected will be notified through GSM. The one who is monitoring from the base station, takes the further decisions.
Advancing the current warfare technologies in the future, these robots ensure proper security at the border areas and also reduces the human threats.

2. LITERATURE SURVEY

[1] Sentry Gun is conceptualized based on the latest research, in which it uses a high resolution camera to scan the target area and movement can be detected by using software. Compared to humans, it shall perform better while operating in autonomous mode, it will bring a significant fall in the death toll and if installed outside every check post, law enforcement agencies and borders, it can be used to its full potential.

[2] Robotics and Automation are led in different divisions in everyday life. It is effectively used to meet the requirements of varying and enduring requirements. The task is intended to build a mechanical vehicle utilizing the cell phone as a control device, connected with a camera and a firearm. The robot alongside the weapon is made to fire consequently in a particular district by identifying the obscure picture of a person and different uncertainties through the assistance of a camera with night vision capabilities. This robot is useful to the Armed Forces for security framework.

[3] The objective is to bring out a new defence mechanism incorporating automation, which will seek to provide a viable solution to improve the security around the border areas and simultaneously reduce the pressure on soldiers. The automation system in this defence mechanism majorly comprises face detection of a human intruder, which is supported by Ultrasonic and IR Sensors. This system is implemented using an Arduino microcontroller, which will be complemented with NodeMCU to provide required wireless communication for sending intruder detection and location information to the cloud, which will trigger the gun to shoot down the enemy. The use of wireless communication over GSM is preferred, because the control stations receive Wi-Fi signals directly from the satellite, which is very reliable and fast. The main objective of our research work is to ensure safeguarding the border region around remote areas, where patrolling is difficult for army personnel and will be implemented by the armed forces.

[4] The main objective of this paperwork was to implement a multi-functional army robot consisting of different sensors. The proposed system consists of a wireless camera for serving the purpose of live video streaming surveillance and a colour sensor which is used as a part of camouflaging feature. In the proposed model, cloud based IoT interface with the Blynk app and Wi-Fi module are used for retrieving, storing and recovering information to increase and improve the range of communication.

[5] This project implements the design and construction of a land mine detector that can detect metals, a gas sensor which can detect toxic gas attacks is used and the robot can be controlled wireless mode through an Android phone. A metal detector circuit interfaced to the control unit, alarms lets the user know about the suspected metal ahead. The metal detector circuit is placed on a robotic vehicle and its operation is to detect metals underneath automatically.

[6] Fire accidents are a disaster that can cause the loss of life, damage of property and permanent disability to the affected victim. They can also suffer from prolonged psychological imbalances and remain in the state of trauma. Therefore, this paper presents the development of a firefighting robot dubbed QRob that can extinguish fire, without the need for the firefighters to be exposed to unnecessary danger. QRob is designed to be compact in size than other conventional fire-fighting robots in order to ease small location entry for in depth reach of extinguishing fire in narrow space. QRob is also equipped with an ultrasonic sensor to avoid hitting any

obstacle and surrounding objects, while a flame sensor is interfaced for fire detection. This resulted in QRob, demonstrating capabilities of identifying the fire locations automatically and ability to extinguish fire remotely at a particular distance. QRob is programmed to find the location of fire and stop at a maximum distance of 40 cm from the fire. A human operator can monitor the actions of the robot by using a camera which connects to an Android phone or remote devices.

[7] This paper has designed the firefighting robot which searches for a fire in a small floor plan or house of specific dimension. There are two dc motors used for motions. There are three sensors used: Temperature for detecting the increase in fire, Smoke (gas) for detection of smoke and IR for detection of obstacles. Apart from increase in temperature the fire is also detected with the assistance of Smoke sensor. The fire is detected with the help of a Smoke sensor present in the system. After detecting fire by the sensor, the firefighting robot will automatically turn on the pump in order to extinguish fire catches. The IR sensor is used for detecting the obstacle in the path of the robot. So that robot can change its direction accordingly after detection. The robot is closely monitored and operated using a web server.

[8] Rescue robots are designed to help humans in search and rescue operations. Rescue robots that are controlled by an operator from a secure distance are called teleoperated robots. In this case, the operator sends command signals to the robot through a communication channel. The robot follows the commands to securely move toward the target locations and, for instance, to manipulate objects or to displace rubbles.

[9] The main objective of this paper is to design a firefighting robot which is capable of detecting the fire outbreak and extinguishes fire using an efficient water spraying system. With the advancement of technology especially in Robotics and incorporating flame sensors it is considerably possible to replace humans with robots for fighting the fire. This would improve the efficiency of firefighters and would also prevent them from risking their lives.

[10] Robots like humanoid, wheeled and armed robots are developed to perform operations such as move and place, object detection, surveillance operation, search and rescue operations. This paper proposed a manually controlled spherical robot system which is implemented using Arduino uno, Camera and Bluetooth. This spherical spy robot can be utilized in the attack and rescue operation to receive the information from the human unreachable areas while doing military services.

3. OVERVIEW OF THE MODEL

As per the previous references, the following are the obtained inferences:

- The sentry gun is developed in both autonomous as well as manual mode. Incorporating the servo motors, the triggering operation is performed.
- In Automation of robots, the implementation of the high resolution night vision cameras are being used, and the mechanical vehicle comprises the robotic firearm, controlled by an Android device.
- The ultrasonic sensor and the IR sensors are interfaced to the Arduino microcontroller and the NodeMCU is used to facilitate uploading the obtained data to the cloud. The control stations receive Wi-Fi signals directly from the satellite, which is very reliable and fast.
- Cloud based IoT interface with Blynk app and Wi-Fi module are used for retrieving, storing and recovering information to increase and improve the range of communication. This serves the purposes like, real time surveillance and colour sensors are used to camouflage with the environment.
- In order to detect the land mines, the metal detectors are used, and the gas detectors are used to detect the toxic gases which are produced after an explosion. These can be controlled by an Android device.

Analyzing the above technicalities, we put forward our methodology wherein, the application of OpenCV is used as an input to take a decision to fire an intruder using Haar cascade classifiers for accurate face detection. In addition to this, we use different sensors to be in sync with actions visioned through the ESP32 camera. In order to detect the landmines, we use the metal detector. We can also incorporate sensors like gas and sound sensors in different parts of the warfield in order to know if any explosions have occurred, based on which the rescue operations can be performed.

4. PROPOSED METHODOLOGY

This project work is about the implementation of Computer Vision using the controls Arduino UNO board. The robot mainly focuses on Surveillance, Automated/Manual firing, Metal detection.

4.1 Surveillance

The robot provides the Surveillance of the war-field using the camera interfaced with the Arduino UNO which is the ESP32 camera module. This operation of Surveillance is done by the robot until it detects a face. The real time data obtained from the surveillance will be seen and be monitored from the base station.

4.2 Firing Action

4.2.1 Manual Firing Action

- The camera does the surveillance operation until it detects any face in its range. When it detects the face, it compares with the pre-trained dataset, to determine whether the person is an invader or not. If the person is found to be an invader, the gun will be pointed at them with the help of servo motors.
- The triggering operation is done manually done from the base station. After the firing of an intruder, the servos will return back to their home position and continue with the surveillance aspect.

4.2.2 Autonomous Firing Action

- When it comes to Autonomous firing, the accuracy to detect the face must be of great concern, as it can bring a threat to the human life.
- The coding related to the rotation of the gun by the servo motors must be altered.
- The servo motor performs the triggering operation.

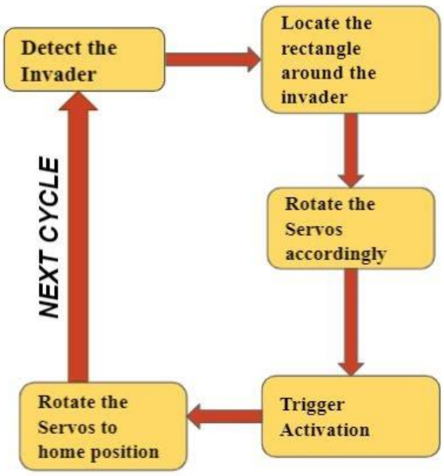

Figure 1: Functional Diagram of Firing Action

4.3 Metal Detection

The robot also performs the operation of metal detection, while on surveillance, if it encounters a land mine, it will notify the base station through GSM, and the location will be tracked with the help of a GPS, so that the hazardous explosions can be avoided without risking a human life.

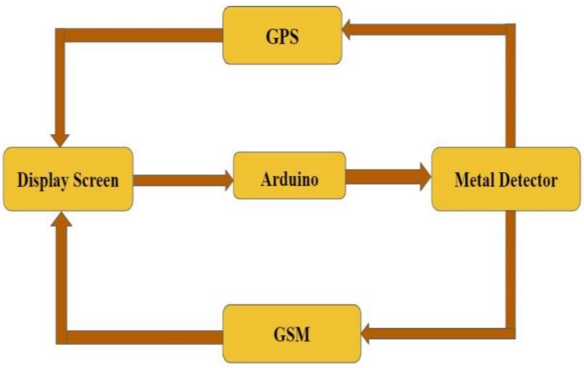

Figure 2: Functional Diagram of Metal Detection

5. CONCLUSION

From the above proposed methodology, an AI vision robot with the advanced capabilities of surveillance, firing, detecting landmines. The advancement of technology in the military field is increasing exponentially. The need for fully automated robots with good accuracy which performs all the actions of the soldiers is in demand. Most of the countries have initiated research on this particular domain. The implementation of new age weaponry now comes with AI embedded technologies. Defense sectors are implementing machine learning to predict and protect from intrusions. From the above factors, it can be observed that the fulfillment of automated robots with good accuracy which performs all the actions of the soldiers will be the future scope.

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Coordination of Charging Plug-in Electric Vehicles (PEV) in Electric Distribution Networks to Minimize Power Losses and Voltage Deviations

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Abstract: Plug-in Electric Vehicle (PEV) is a vehicle with a drive in the form of an electric motor and gets its energy source from a rechargeable battery. PEV (grid-to-vehicle, or G2V) charging activity can pose a risk to the distribution system when PEV is injected into the system. Charging PEV in the distribution system will cause the demand for electrical power to increase. Without a proper and optimal charging coordination system for the many PEVs that exist in the distribution network system, the following technical problems will arise in the network such as: occurrence of unusual and unwanted peak loads in power consumption, voltage sag, transformers or conductors overload, as well as the occurrence of high power system losses in the distribution system. This study discusses the optimization of PEV charging coordination scheduling in a distribution system by considering power losses and voltage deviations. To optimize the coordination of PEV charging, this study used a metaheuristic method called the Binary Particle Swarm Optimization (BPSO) which was then compared with the Binary Gray Wolves Optimization (BGWO) method. This scheme is simulated on the 20kV Pujon Feeder distribution system in Malang, Indonesia. The initial simulation results, at the time when the most loads were presented, showed 80 percent of PEV penetration, increase in power losses of 54.51 percent and voltage deviation of 9.82 percent. By using the BPSO method, the results showed power loss increase of 27.2 percent and voltage deviation of 7.75 percent. Meanwhile, by using the BGWO method the increase in power losses was 31.09 percent and the voltage deviation was 7.98 percent.

Keywords: plug-in electric vehicle; optimization; charging coordination; distribution network; power loss

1. INTRODUCTION

Plug-in Electric Vehicle (PEV) is a vehicle with an electric motor which gets energy from a rechargeable battery. Therefore, this vehicle produces low emissions which reduce pollution. PEV can be a more promising option as a way to reduce emissions of greenhouse gases (GHGs). In addition, PEV's lower daily operating costs compared to conventional vehicles with internal combustion engines have attracted the attention of vehicle users [2]. In the last decade, PEV vehicles have developed a very substantial industry in developed countries such as the United States, Japan, and Europe. Several well-known brands of vehicle manufacturers have also started to market several types of plug-in electric vehicles (PEV) globally, including to the Indonesian people.

Basically PEV utilizes a large battery capacity and requires charging to provide sufficient energy as a source of energy for high-power electric motors. PEV batteries can be charged at home or other commercial locations through charging stations in public facilities [3]. PEV is considered as an additional electrical load on the distribution system. PEV (grid-to-vehicle, or G2V) charging activity can pose a risk to the distribution system when injected into the system. Charging PEV in the distribution system will cause the demand for electrical power to increase. Without a proper and optimal charging coordination system for the many PEVs that exist in the distribution network system, technical problems will arise in the network such as: occurrence of unusual and unwanted peak loads in power consumption, occurrence of voltage sag, overloading of transformers or conductors, as well as the occurrence of high power system losses in the distribution system [4]. Therefore, an optimal PEV charging coordination system is needed to avoid these problems.

To overcome the problems when PEV is injected into the distribution system, increasing the power generation capacity is a feasible solution but it is not economical because the required infrastructure is too large. Another available solution is smart grid deployment which can increase system reliability by coordinating PEV charging operations. Several studies have also discussed the problem of coordinated PEV charging with different objectives such as the following: Optimization of PEV charging by reconfiguring the existing distribution network method [8]; Coordination of PEV charging to minimize power losses and improve voltage stability using the Real Time Smart Load Management algorithm [4]; Optimization of the PEV charging schedule using a heuristic method in the form of a genetic algorithm [1]. The aforementioned literatures discuss many aspects of PEV coordination problems in distribution systems. However, only a few studies have analyzed power losses and voltage stability as issues that are discussed at once. In addition, to the best of the knowledge of the authors of this thesis, no research has been conducted to analyze power losses as well as voltage deviation in the distribution network during PEV charging by considering optimization of PEV charging scheduling using metaheuristic methods.

This research focuses on the optimization of PEV charging coordination scheduling in distribution system by considering power losses and voltage deviation. This PEV charging coordination takes advantage of the PEV charging timings in the distribution system. To optimize the coordination of PEV charging, this study used a metaheuristic method called Binary Particle Swarm Optimization (BPSO) which were then compared with the Binary Gray Wolves Optimization (BGWO) method.

2. PROBLEM FORMULATION

2.1 Objective Function

The main focus of this research is to determine the optimal PEV charging schedule with the aim of minimizing power losses and voltage deviation. To simulate the coordination of PEV charging, the PEV charging time approach is carried out every 10 minutes (144 timeslots in 24 hours). The planned strategy for optimization of PEV charging coordination is optimization of PEV charging scheduling (in time intervals of every 10 minutes). The objective function of the optimization process to carry out the planned method is shown in Equation (1).

$$minf = \sum_{h}^{24}(\mathrm{P}_{loss} + V_d) \quad (1)$$

P_{loss} is the ratio of power losses before and after PEV charging coordination. And V_d is the maximum voltage deviation in the distribution system. The P_{loss} value is calculated from the comparison of the total power losses after and before the coordination is carried out as shown in Equation (2).

$$\mathrm{P}_{loss} = \frac{P_{loss}^{coord}}{P_{loss}^{uncoord}} \quad (2)$$

The equation for power losses in the distribution system is shown in Equation (3).

$$P_{loss} = \sum_{t=1}^{\text{timeslot}} \left(I_{j,t}^2 \times R_j\right) \quad (3)$$

The voltage deviation (V_d) can be calculated from the difference between the nominal voltage value and the measured voltage. The smaller the value of the voltage deviation from the nominal voltage in a bus on the distribution network, the better the state of the voltage on the system. The calculation of the voltage deviation can be shown from Equation (4).

$$V_d = Max_{i=2}^{m}\left(\frac{V_{rated} - V_i}{V_{rated}}\right) \quad (4)$$

V_{rated} is the nominal voltage in the system which is 1.0 pu. V_i is the voltage on the *i*-th bus, and *m* is the total number of buses in the system.

2.2 Constraints

In the whole optimization process, some limitations or constraints on the system also need to be considered. Some of these constraints include:

- Maximum Load

$$P_{demand}^{max} \geq \sum_{i=2}^{n}(P_{load} + P_{PEV})_i \quad (5)$$

Description:

n : the number of buses in the system

P_{load} : housing load

P_{PEV} : load of PEV

i : *i*-th bus

P_{demand}^{max} : maximum load on distribution transformer for 24 hours

- Bus Voltage

$$V_{min} \leq V_i \leq V_{max} \quad (6)$$

Description:

V_{min} dan V_{max} : the minimum and maximum voltage ranges allowed in the system

V_i : voltage on bus *i*

The value of the voltage limit range in this study is set at ±10% of the nominal voltage, which is 0.9 - 1.1 pu.

3. ALGORITHMS AND IMPLEMENTATION

3.1 Binary Particle Swarm Optimization (BPSO)

In this study, Binary Particle Swarm Optimization (BPSO) was applied to complete the PEV charging coordination optimization method. The main difference between BPSO and PSO is only in the equation for changing the position of the particles. The equation for the velocity of each particle is shown in Equation (7) and the equation for the change in position for each particle is shown in Equation (8). All particles move in d-dimensional space.

$$vel_{i,d}^t = w^t vel_{i,d}^t + c_1 r_1\left(pbest_{i,d}^t - x_{i,d}^t\right) + c_2 r_2\left(gbest_{i,d}^t - x_{i,d}^t\right) \quad (7)$$

Description:

$vel_{i,d}^t$: velocity of particle *i* in dimension *d* during time *t*

$x_{i,d}^t$: the position of particle *i* in dimension *d* during time *t*

c_1 dan c_2 : *cognitive constant* and *social acceleration*

r_1 dan r_2 : random values distributed between 0 dan 1

$$x_{i,d}^{t+1} = \begin{matrix} 0 \; rand() \geq sig(vel_{i,d}) \\ 1 \; rand() < sig(vel_{i,d}) \end{matrix} \quad (8)$$

$$sig(vel_{i,d}) = \frac{1}{1+e^{-vel_{i,d}}} \quad (9)$$

In Equation (9), $sig(vel_{i,d})$ is the equation of the logistic function transformation and $rand()$ is a random value distributed between "0" and "1". BPSO was chosen in this study because of the nature of the solution required. BPSO provides a final solution in the form of binary "1" or "0", which indicate charging and off-charging conditions in the PEV charging process, respectively.

The steps in the flow chart in Figure 1 can be used to determine the optimal coordination of PEV charging using the Binary Particle Swarm Optimization method. All constraints in the system are also considered at this stage.

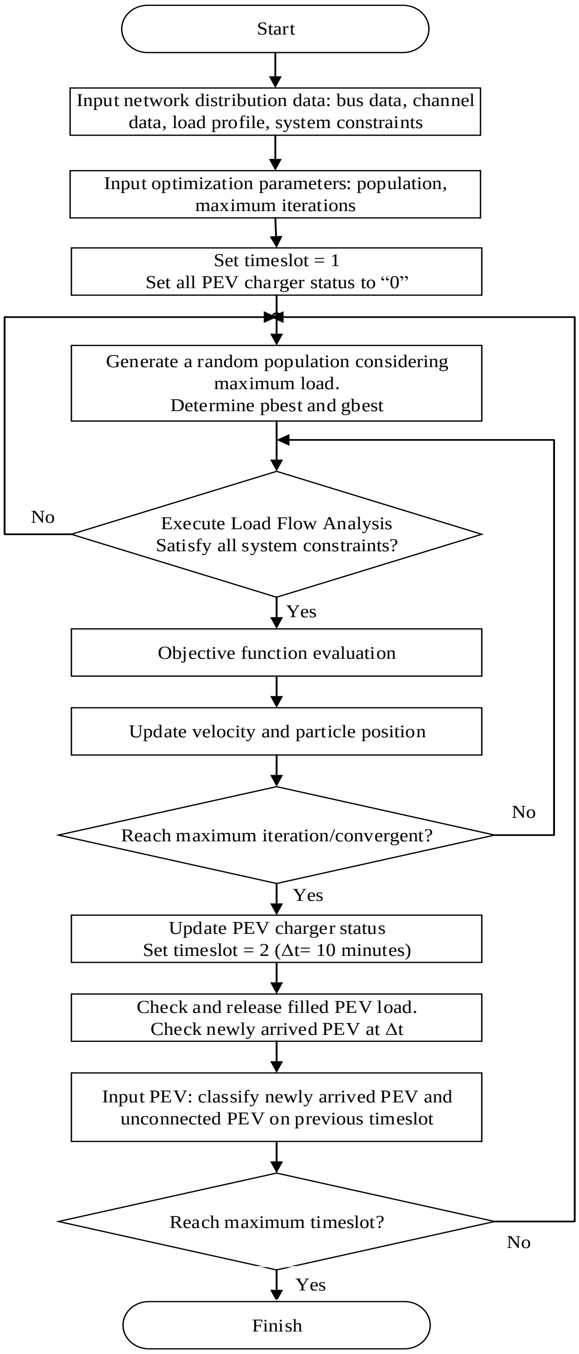

Figure 1. Flowchart of PEV charging coordination optimization using BPSO method

3.2 Binary Grey Wolves Optimization (BGWO)

The GWO algorithm is designed to solve continuous optimization problems. For binary optimization problems such as feature selection, a binary version of the GWO is required. In 2016, Emary developed the Binary Gray Wolves Optimization algorithm to solve the feature selection problem. The equation for the change in position in the BGWO is shown in Equation (10).

$$X(t+1) = Crossover(Y_1, Y_2, Y_3) \tag{10}$$

$Crossover(Y_1, Y_2, Y_3)$ is a crossover operation between solutions, while Y_1, Y_2, and Y_3 are binary vectors affected by the movement of the alpha, beta, and delta wolves. In this BGWO, the values of Y_1, Y_2, and Y_3 are calculated using Equation (11) to Equation (13).

$$Y_1^d = \begin{cases} 1, if\,(X_\alpha^d + bstep_\alpha^d) \geq 1 \\ 0, otherwise \end{cases} \tag{11}$$

$$Y_2^d = \begin{cases} 1, if\,(X_\beta^d + bstep_\beta^d) \geq 1 \\ 0, otherwise \end{cases} \tag{12}$$

$$Y_3^d = \begin{cases} 1, if\,(X_\delta^d + bstep_\delta^d) \geq 1 \\ 0, otherwise \end{cases} \tag{13}$$

In Figure 2, a PEV charging optimization flow chart is shown using the Binary Gray Wolves Optimization method. This step can be used to determine the optimal coordination of PEV charging with the aim of minimizing power losses and voltage deviations simultaneously. All constraints in the system are also considered at this stage.

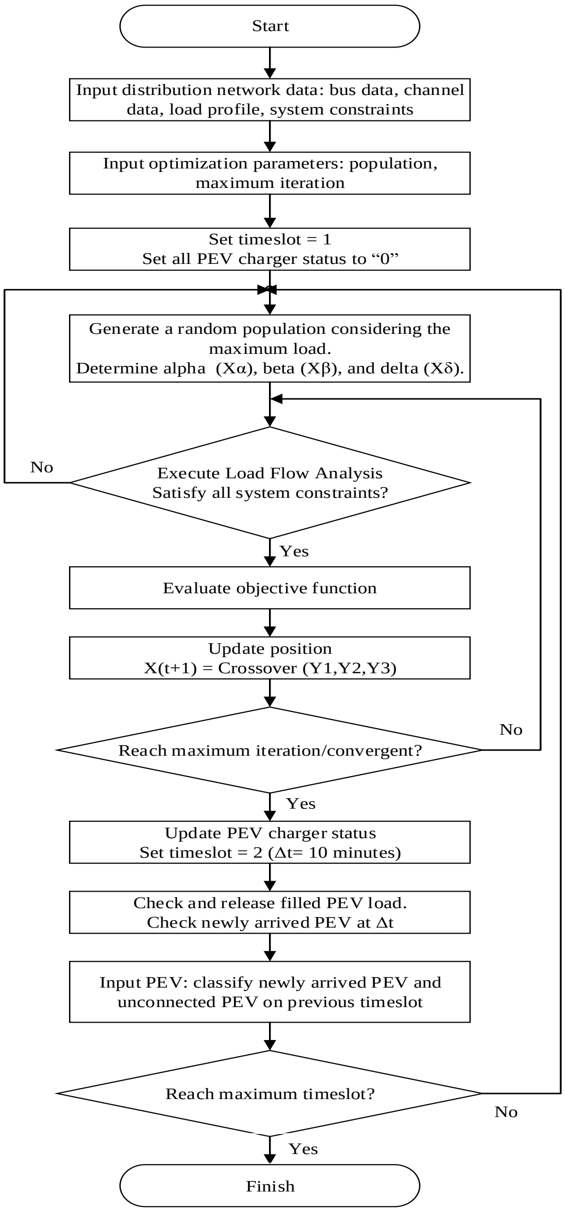

Figure 2. Flowchart of PEV charging coordination optimization using BGWO method

4. RESULTS AND DISCUSSION

4.1 Existing System Flow Analysis Prior to Optimization of PEV Charging Coordination

The power flow analysis of the existing system is carried out when there is already PEV penetration but the optimization process for PEV charging coordination has not been carried out. In this study, 4 cases of PEV penetration will be analyzed. Namely PEV penetration in the system for penetration values of 20%, 40%, 60%, and 80%. This PEV penetration value is based on the added value of the total load in the Pujon feeder which is burdened by the existing household load. For the loading value of 1 unit of PEV in accordance with the limitations of this research problem, namely PEV with the maximum required charging power specification of 4.4 kVA. PEV are distributed according to buses located in densely populated areas or buses with sufficient transformer capacity to accommodate the additional PEV load. The results of the analysis of the existing load power flow after the penetration of PEV in the 24-hour time interval is shown in the graphs shown in Figures 3 to 5.

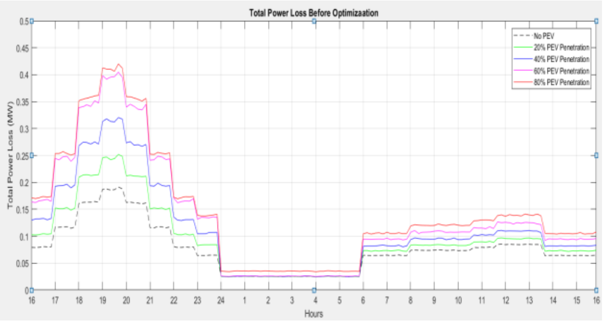

Figure 3. Total power loss before optimization

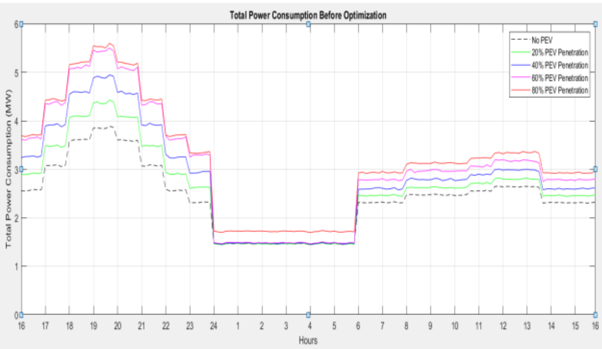

Figure 4. Total power consumption before optimization

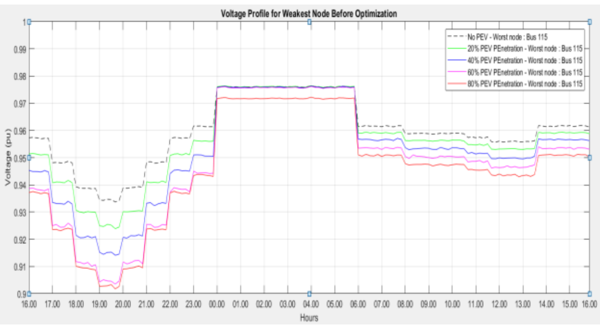

Figure 5. Voltage profile for weakest node before optimiztion

In this scenario, the PEV charging process starts as soon as the PEV is connected to a charging device. PEVs that are connected within a certain time are filled in randomly regardless of the constraints in the existing distribution system. Therefore, the existing system faces more problems such as overload in the distribution system, high power losses and voltage degradation. The total value of power losses in a 24-hour time interval is shown in Figure 3. It was found that this random and uncoordinated PEV charging process causes power losses to increase, especially during peak hours, the maximum load occurs from 20.00 to 23.00. With the highest value of power losses at 80% penetration of 0.42 MW occurring at 19.40. Figure 4 shows that the total loading power also increases when the PEV penetrates. The total loading power is relatively high in the presence of PEV penetration. The highest total loading power value occurs when the penetration of 80% PEV is 5.6 MW at 19.40. In Figure 5 it is shown when the PEV penetration is at 60% and 80%, with the lowest stress value of 0.9 pu. Meanwhile, at 20% and 40% PEV penetration, the lowest stress values were still within the permissible limits, which were 0.92 and 0.91 pu.

The value of the power loss after the penetration of the PEV load can be used as a reference for the optimization of PEV charging scheduling coordination considerations. This is because when there is penetration of the PEV load, the existing system conditions cause an increase in the value of power losses and an indication of a lower voltage profile, with an average of below 0.95 p.u. Meanwhile, the permissible voltage profile according to SPLN 1: 1995 is 0.90 p.u ≤ Vbus ≤ 1.1 p.u.

4.2 Optimization of PEV Charging Coordination with Binary Particle Swarm Optimization Algorithm

The BPSO algorithm is the first algorithm used in the optimization of PEV charging coordination. The first step after entering the load data and channel data into Newton Raphson's calculations was to determine the penetration limit of the PEV distributed into the system. The second step was to enter the initial parameters used in the optimization process using BPSO. The third step was to run optimization in 4 cases of PEV penetration to obtain an analysis of conditions in the system in sharing cases of PEV penetration.

To overcome the adverse effects of uncoordinated PEV charging on the distribution network, a real-time PEV charging coordination approach based on 10-minute intervals was proposed in this study. When the PEV is connected to a charger, the PEV will not be charged immediately as long as the charging decision is not taken by the control center. The optimally implemented BPSO algorithm schedules the arriving PEV and can meet all system constraints. This coordination strategy is more advantageous for the existing distribution system compared to the case of uncoordinated PEV charging. Figures 6 to 8 show the results of the system power flow analysis after optimization using BPSO.

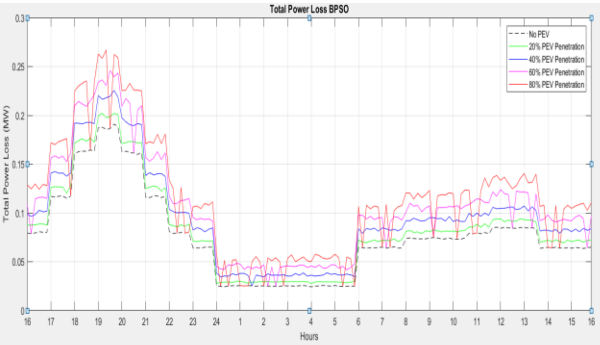

Figure 6. Total power loss system using BPSO algorithm

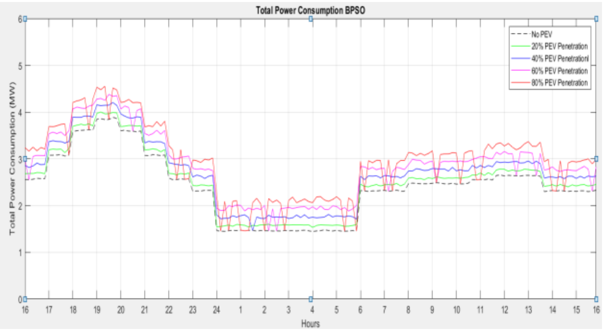

Figure 7. Total power consumption using BPSO algorithm

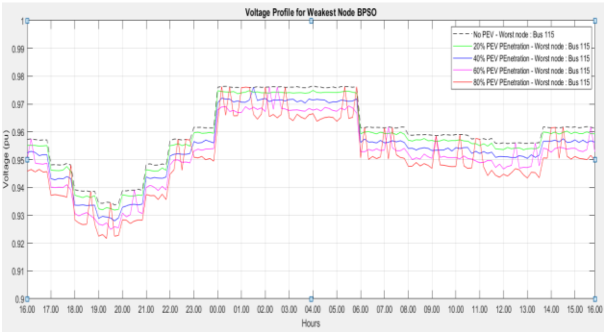

Figure 8. Voltage profile for the weakest node using BPSO algorithm

Figure 6 shows that the highest value of power losses occurs when the 80% PEV penetration can be reduced from 0.42 MW to 0.26 MW. Likewise, the total power consumption and voltage on the system can also decrease after optimization using BPSO. This is shown in Figure 7, with the highest total power consumption of 4.51 MW, while and Figure 8 shows the lowest voltage of 0.92 pu.

4.3 Optimization of PEV Charging Coordination with Binary Gray Wolves Optimization Algorithm

The BGWO algorithm is the second algorithm used in the optimization of PEV charging coordination. The first step after entering the load data and channel data into Newton Raphson's calculations was to determine the penetration limit of the PEV distributed into the system. The second step was to enter the initial parameters used in the optimization process using BGWO. The third step was to run optimization in 4 cases of PEV penetration to obtain an analysis of conditions in the system in sharing cases of PEV penetration.

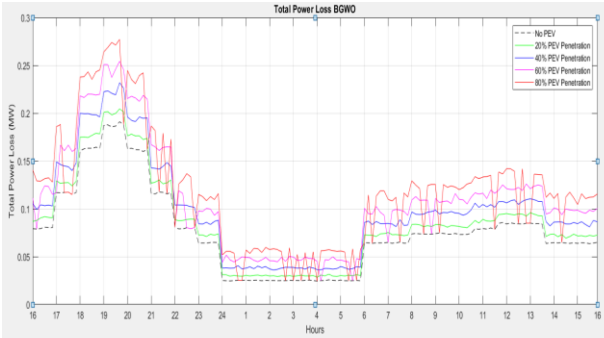

Figure 9. Total power loss system using BGWO algorithm

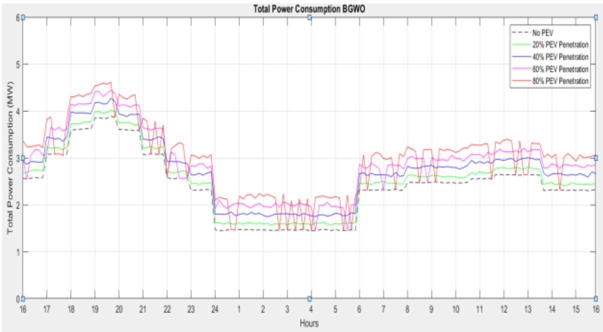

Figure 10. Total power consumption using BGWO algorithm

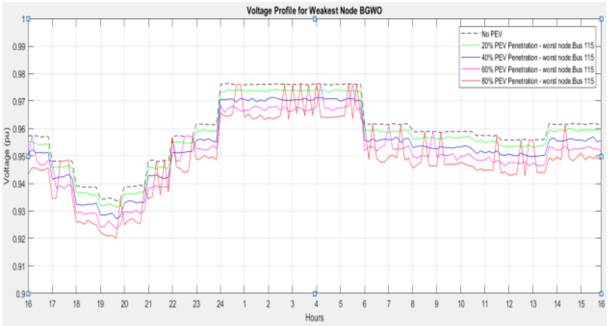

Figure 11. Voltage profile for the weakest node using BGWO algorithm

Figure 9 shows that the value of power losses that occur during PEV penetration can be reduced unlike before the optimization process. In the case of 80% penetration, the power losses can be reduced to 0.28 MW. The total power consumption in Figure 10 shows that it has also decreased to 4.61 MW. Likewise, the voltage value in all cases of PEV penetration also decreased, as in 80% penetration the voltage value at the worst node became 0.92 pu.

4.4 Comparative Analysis of BPSO and BGWO Algorithms

The simulation results of the PEV charging coordination power flow analysis using the BPSO and BGWO algorithms are summarized in Table 1. It can be seen that the total power losses can be reduced for all PEV penetration levels when the PEV charging coordination optimization process is carried out. It can also be observed that the overall voltage profile of the network increases. In addition, in terms of power consumption and power losses, network performance improved.

Table 1. Impact of PEV charging on distribution systems in various cases

Scenario	PEV Penetration(%)	Δ V (%)	Increase in loss[a] (%)
No PEV	0	6,63	0
Uncoordinated Charging	20% PEV penetration	7,61	24,16
	40% PEV penetration	8,58	40,36
	60% PEV penetration	9,65	52,80
	80% PEV penetration	9,82	54,51
Coordinaed Charging using BPSO	20% PEV penetration	6,81	5,45
	40% PEV penetration	7,20	15,35
	60% PEV penetration	7,41	20,24
	80% PEV penetration	7,75	27,20
Coordinaed Charging using BGWO	20% PEV penetration	6,86	6,58
	40% PEV penetration	7,28	17,62
	60% PEV penetration	7,65	24,89
	80% PEV penetration	7,98	31,09

[a]Increase in loss compare to no pev case

5. CONCLUSION

In distribution systems, uncoordinated and random PEV charging activity results in overloading of distribution transformers, severe voltage deviation, and significantly increased system power losses. Therefore, the main objective of this study is to develop an optimal PEV charging process. The results of this study show that the use of the BPSO and BGWO algorithm methods is able to produce PEV charging coordination with significantly decreased power losses and voltage deviations compared to uncoordinated PEV filling.

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Analysis of the Compatibility of Student Satisfaction Index with Course Value Using Significance Correlation and Backpropagation Approach

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Abstract: The implementation of the measurement of customer satisfaction is the measurement of service satisfaction of lecturers to students to lecturers carried out by the State Islamic University of Maulana Malik Ibrahim Malang during the pandemic using the IKM Online application. The competencies measured are pedagogic competence, professional competence, personality competence, and social competence. The measurement of the correlation of significance to the results of IKM Online compared with student scores as learning outputs is carried out to determine the relationship between the two variables. The coefficient of determination is also added to the measurement to determine the strength of the influence of one variable on another variable. The results show that the correlation between the 2 variables is strong and the subject value variable has an effect of 55.9504% on the IKM outcome variable. The data classification process using the backpropagation algorithm is used to strengthen the relationship between the two variables. The result is the 2-5-1 model with RMSE 0.028 being the best model and the strong data class being the first class. From this study, measurements are needed to determine other factors that affect the assessment of student satisfaction to lecturers and evaluation of survey instruments.

Keywords: satisfaction survey, IKM online, correlation, significance, coefficient of determination, backpropagation

1. INTRODUCTION

Customer satisfaction is one of the determining indicators to determine whether the business processes carried out by a business unit have been successful or not. The more satisfied with the goods or services provided to customers, the better the products presented to customers [1]. Therefore, it is not surprising that customer satisfaction always gets special attention when formulating a business strategy [2].

The measurement of service satisfaction is not without questions. The results of the evaluation conducted by the Quality Assurance Institute (LPM) of State Islamic University of Maulana Malik Ibrahim Malang found that there were doubts about the results of the satisfaction survey. The doubts are related to whether the survey results are in line with the performance of the lecturers who are being assessed [3]. Whether the survey respondents gave an assessment of the value they received. Then whether the assessment is carried out randomly without looking at the aspects measured in the survey, given the pandemic conditions resulting in direct interaction of lecturers and students in the learning process cannot be carried out. Then whether it is in accordance with the aspects measured.

To answer this question, it is necessary to carry out several analyzes, one of which can be done is to analyze the relationship between the results of measuring student satisfaction with lecturer services and the value of the courses obtained by students as the output of learning (learning output) with the correlation significance method. [4]. Comparing the behavior pattern approach with this student score variable, a value approach will be obtained which will describe whether or not there is a correlation between the two. Tracing the pattern of respondent behavior that can be tracked through filling out the survey. From this classification, a behavioral model of survey respondents will be obtained and to compare it with the measured correlation results.

The search for data classification is by measuring variables such as the Student Satisfaction Index (IKM) which is measured using the IKM Online application, the value of students as learning outcomes with the variable of the course lecturer. The method used to classify these variables is an artificial neural network approach with the Backpropagation method. Although it has several weaknesses, such as training results that are not constant and it is not known in detail how the prediction results are obtained, because this method cannot provide information about the most influential weights among the input patterns, this method also has advantages. The advantages of this method are that it is able to formulate the experience and knowledge of forecasters, and is very flexible in changing forecasting rules [5].

The object in this study is the result of a survey of lecturer service satisfaction to students in the Covid-19 pandemic condition using the IKM Online application at UIN Maulana Malik Ibrahim Malang in the odd semester of 2020/2021. The purpose of this study is to measure the level of correlation between the implementation of the measurement of lecturer service satisfaction to students compared to learning outcomes in the form of academic values with the correlation significance method and artificial neural networks. This study is also intended to find the relationship between the two variables and perform a classification process on the measurement results. The results of these measurements are also to determine whether there is a correlation between the measurement of service satisfaction of lecturers and students with the learning process. With this research, it is expected to be able to answer the results of the evaluation findings and an improvement in the measurement of IKM and the quality of learning at State Islamic University of Maulana Malik Ibrahim Malang in the future [6].

2. METHOD

The concept of this research method is as illustrated in Figure 1 below:

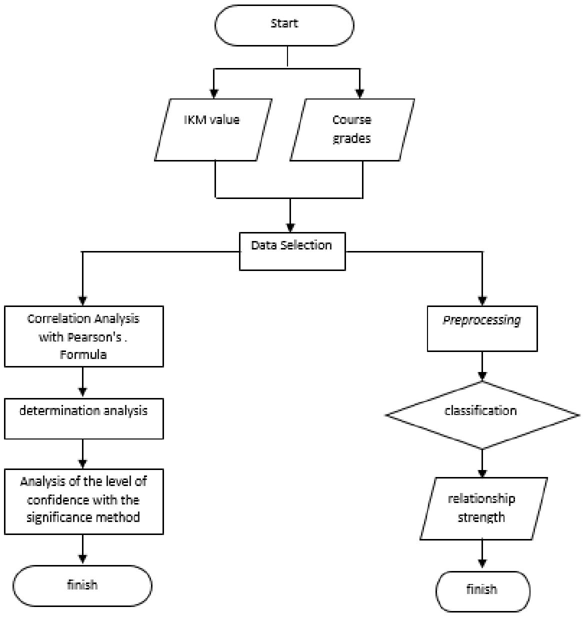

Figure 1. Research Method

2.1 Data Selection

Data selection is the initial stage in preparation before the data is analyzed [7]. In the data selection, the IKM result data is taken for the nim variable, the IKM value, the course code and the lecturer code. The student value data is taken for the variable nim, course value, course code and lecturer code. The results of this data selection are data tables for nim, ikm value, mk value, mk code, lecturer code.

2.2 Preprocessing

Preprocessing is the initial stage for classification analysis. At this stage the attributes and data classes are determined. The data is then normalized so that the normalized data is ready to be processed into the system.

2.3 Correlation Coefficient of Significance and Determination

This is the most widely used correlation analysis formula, which measures the strength of the 'linear' relationship between the raw data of the two variables, rather than their ranking [8]. This formula is a dimensionless coefficient, meaning that there are no data-related limitations to consider when performing an analysis with this formula, which is the reason why this coefficient is a suitable formula to use [9].

$$r = \frac{n\sum x_i\, y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i{}^2\,(\sum x_i)^2}.\sqrt{n\sum y_i{}^2\,(\sum y_i)^2}}$$

Where x is the IKM result variable and y is the subject value variable. the resulting measurement will be in numerical form generated by all correlation coefficients, including Spearman's Rank and Pearson's Coefficient: $-1 < r < +1$.

The method described above should be used according to whether there are parameters associated with the data collected or not. Two terms to pay attention to are:

a. Parametric: (Pearson's coefficient) Namely where data must be handled in terms of population parameters or probability distributions. Usually used with quantitative data already defined in the parameter.
b. Nonparametric: (Spearman's Rank) That is where no assumptions can be made about the probability distribution. Usually used with qualitative data, but may be used with quantitative data if Spearman's Rank proves inadequate.

The correlation coefficient, *r*, provides only a measure of the strength and direction of a linear relationship between two variables. However, it does not provide information about the proportion of variation (variation) of the dependent variable (Y) that can be explained or caused by a linear relationship with the value of the independent variable (X). The value of r cannot be directly compared, for example we cannot say that the value of $r = 0.8$ is twice the value of $r = 0.4$. However, the squared value of r can accurately measure the ratio/proportion, and this statistical value is called the Coefficient of Determination, r^2. The coefficient of determination can be defined as a value that expresses the proportion of variance Y that can be explained/explained by a linear relationship between variables X and Y.

The level of significance, also known as alpha or , is a measure of the strength of the evidence that must be present in a study sample before the researcher rejects the null hypothesis and concludes that the effect is statistically significant. Researchers determine the level of significance before conducting the experiment. The level of significance is the probability of rejecting the null hypothesis even though the hypothesis is true. Significance can be measured by the equation:

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}}.$$

where n is the number of samples and r is the Pearson's correlation.

2.4 Artificial Neural Network

An artificial neural network (ANN) or also called a Neural Network is a network of a collection of small-level processing units that are described based on a biological nervous system. An artificial neural network can change its structure in order to solve a problem based on information obtained both internally and externally through the system, so it is also called an adaptive network because of its adaptive capabilities [10]. This Artificial Neural Network is determined by 3 things, namely:

1. The pattern of relationships between neurons or so-called network architecture
2. Algorithm which is a method for determining the weight of the link or link or can also be called the training process
3. Activation function

An artificial neural network is a mathematical model that defines the function $f: X \rightarrow Y$. The network in this system is an interconnection of neurons that are in different layers. The layers in the ANN are divided into 3, namely:

1. Input layer or input layer.
2. Hidden layer or hidden layer.
3. Output layer or outer layer.

Mathematically, a neuron is a function that receives input from the previous layer $g_i(x)$ (i layer). This function generally processes a vector and then converts it to a scalar value, as the equation $f(x) = K(\Sigma i\ w_i\ g_i\ (x))$, where K is a special function which is often called the activation function and w is the load or weight.

In classification, there are several methods that can be used to classify them [9]:

1. Artificial Neural Network (ANN)
2. Naive Bayes
3. Support Vector Machine (SVM)
4. Decission Tree
5. Fuzzy

Each method has advantages and disadvantages and also different specifications for each use, one of which is a data object. The use of methods with different object types will result in different optimizations.

2.5 Backpropagation

Backpropagation is one of the learning algorithms in Artificial Neural Networks [11]. The learning mechanism in backpropagation is done by adjusting the ANN weights in a backward direction based on the error value in the learning process. Backpropagation consists of three layers, namely the input layer, hidden layer and output layer.

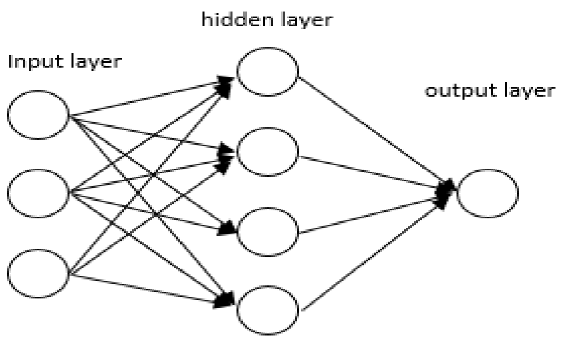

Figure 2. Backpropagation algorithm architecture

2.5.1 Advantages and Disadvantages of Backpropagation Algorithm

This backpropagation algorithm also has advantages and disadvantages. Among the advantages of this algorithm are [12]:

a. Can be implemented in solving a problem related to identification, prediction, pattern recognition and others.
b. Have the ability to learn and be immune to mistakes, so as to form a system that is resilient and can work consistently.
c. In the training process, the network can get a balance so that it is able to provide the correct response to input patterns such as the patterns used during training.

The disadvantages of this algorithm are:

a. The learning rate parameter can vary according to the condition of the error change in each iteration.
b. It takes a long time in the learning process to arrive at the convergent level.
c. The calculation of the weight change of the algorithm is able to cause a local minimum, thus causing instability.

2.5.2 Backpropagation Training

Backpropagation algorithm training is carried out to get the desired result estimate [13]. Some steps in backpropagation algorithm training are as follows [14]:

Step 1: Initialize the weights with the smallest random number

Step 2: As long as the stop condition is false, do steps 3 – 9

feed forward process

Step 3: Each input unit (x_i, i = 1,…, n); receive input signal and forward the signal to all hidden layers.

Step 4: Each hidden unit (z_j, j = 1,…, p); add up the weights of the signals input signal (including bias)

$$z\_in_j = v_{0j} + \sum_{i=1}^{n} (x_i . v_{ij})$$

then calculate the output signal from the hidden layer using the activation function count z_j = f (z_in_j). This output signal is then sent to all layers in the output layer.

Step 5: Each output (y_k, k = 1,…, m); summing the input signal weights:

$$Y\_in_k = w_{0j} + \sum_{k=1}^{p} (z_j . v_{jk})$$

then calculate the output signal from the hidden layer using the activation function count $Yj = f(Y\_in_k)$. This output signal is then sent to all layers in the output layer.

Process feedback (backward)

Step 6: Each unit of output (y_k, k = 1,…, m); receive a pattern according to the input training, to calculate the error between the target and the output generated network;

$\delta_k = (t_k - y_k) f'(y_{in_k})$

The factor δ_k is used to calculate the error correction w_jk which will later will be used to fix w_{jk}

$\Delta w_{jk} = \alpha \delta_k z_j$

Also count w_ok to fix w_{ok}

$\Delta w_{ok} = \alpha \delta_k$

Step 7: Each hidden unit (Zj, j = 1,…, p); summing input delta from previous step

$$\delta\_in_j = \sum_{k=1}^{m} \delta_k w_{jk}$$

Then calculate the weight correction with $v_{ij}=\alpha\delta_j\, x_i$ and calculate the correction bias using $v_{oj}=\alpha\delta_j$.

Step 8: Each output unit (Yk, k = 1,…, m); fix the weight and bias of hidden layer (j = 0,…, p) where w_{jk} (new)=w_{jk} (old) + w_{jk}

Step 9: The test stops when an error is found and training is stopped.

3. RESULT AND DISCUSSION

3.1 Data Selection

The data selection process is carried out after data collection. The data taken is data on the results of online IKM in the odd semester of 2020/2021 and data on the value of students in the odd semester of 2020/2021 taken from the online SIAKAD application. From these data, information is obtained in the IKM data there are 794,535 rows of student entries. As for the student value data obtained as many as 135,536 rows of data. The two data above are then queryed using PHP and MySql applications as shown below.

id	nim	kode_mk	nilai_mk	kode_dosen	nilai_ikm
1	17520099	952305	3	51060	4,0
2	17520074	952315	8	52026	4,5
3	17520014	952405	5	51053	4,0
4	17520046	952405	1	51053	5,0
5	16510086	1051215	7	51001	5,0
6	16510120	1051215	3	51001	4,0
7	16510140	1051215	7	51001	5,0
8	17510103	1051215	7	51001	4,0
9	17510118	1051215	9	51001	4,5
10	17510224	1051215	1	51001	3,0
11	15510130	1051306	8	51086	5,0
12	17510027	1051308	1	51077	3,0
13	17510027	1051314	1	51024	3,0
14	16510075	1051314	6	51024	3,1
15	16510086	1051314	3	51024	5,0
16	16510120	1051314	1	51024	3,5
17	17510145	1051317	9	51082	4,0
18	17510224	1051317	9	51082	3,5
19	16510086	1051317	9	51082	5,0
20	17510081	1051318	8	51006	5,0
21	17510145	1051318	8	51006	4,0
22	17510143	1051402	7	51012	2,6
23	17510170	1051402	9	51012	3,0
24	17510196	1051402	5	51012	3,0
25	16510086	1051402	6	51012	5,0
26	16510086	1051406	3	51014	5,0
27	14660064	1266503	6	66010	3,1
28	15660073	1266503	1	66007	4,0
29	16660020	1266503	8	66007	4,8
30	16660122	1266503	1	66007	5,0
31	16660123	1266503	1	66010	4,0
32	16540050	1354213	8	51069	2,2
33	18540114	1354213	8	51069	4,8
34	18540115	1354213	8	51069	4,0
35	18540114	1354318	3	54007	4,7
36	18540065	1354404	8	51061	4,0
37	18540056	1354405	8	51021	3,9
38	17540082	1354408	5	54014	5,0
39	14210058	1421223	8	21075	3,0
40	17210156	1421227	8	21057	3,0
41	17210190	1421412	8	21007	3,0
42	17210110	1421500	9	21010	3,0
43	18220066	1422233	5	20002	5,0

Figure 3. Data processing results

Processed data obtained through data selection were analyzed by correlation method with Pearson's formula. The correlation results from data processing using PHP and MySQL above are

r = 0.748

and the coefficient of determination is obtained

$r^2 = 0.559504$

The significance obtained with the equation below and processed with the script above is:

t=(r-√(n-2))/√(1- r^2)

=(0.748-√(58024-2))/√(1- 0.559504)

This calculation illustrates that the close relationship of these two variables is 0.748 or 74.8%. To determine the effect of one variable with other variables, it can be used to calculate the coefficient of determination. From the calculation using the coefficient of determination equation obtained r2 = 0.559504. This means that the variable value of the course has an influence relationship on the IKM outcome variable of 0.559504 or 55.9504%. This condition shows that the results of the IKM survey are only influenced by the variable value of 55, 9504%. The other 44.0496% are influenced by other variables.

3.2 Preprocessing

This process is a process to prepare data before classification. Merged data is normalized. Data is also processed to determine variables and classes for mapping. Normalization of data is done with PHP and MySql applications using the equation:

X’=0,8(X-b)/((a-b))+0,1

Where:

X' = normalized data

X = original data/data to be processed

a = maximum value of original data

b = minimum value of original data

The results of processing the data are partially illustrated in Figure 5 below.

id	nim	kode_mk	kode_dosen	nilai_mk	nilai_ikm
1	17520099	952305	51060	0,3	0,7
2	17520074	952315	52026	0,8	0,8
3	17520014	952405	51053	0,5	0,7
4	17520046	952405	51053	0,1	0,9
5	16510086	1051215	51001	0,7	0,9
6	16510120	1051215	51001	0,3	0,7
7	16510140	1051215	51001	0,7	0,9
8	17510103	1051215	51001	0,7	0,7
9	17510118	1051215	51001	0,9	0,8
10	17510224	1051215	51001	0,1	0,5
11	15510130	1051306	51086	0,8	0,9
12	17510027	1051308	51077	0,1	0,5
13	17510027	1051314	51024	0,1	0,5
14	16510075	1051314	51024	0,6	0,514285714
15	16510086	1051314	51024	0,3	0,9
16	16510120	1051314	51024	0,1	0,6
17	17510145	1051317	51082	0,9	0,7
18	17510224	1051317	51082	0,9	0,608571429
19	16510086	1051317	51082	0,9	0,9
20	17510081	1051318	51006	0,8	0,9
21	17510145	1051318	51006	0,8	0,7
22	17510143	1051402	51012	0,7	0,42
23	17510170	1051402	51012	0,9	0,5
24	17510196	1051402	51012	0,5	0,5
25	16510086	1051402	51012	0,6	0,9
26	16510086	1051406	51014	0,3	0,9
27	14660064	1266503	66010	0,6	0,52
28	15660073	1266503	66007	0,1	0,7
29	16660020	1266503	66007	0,8	0,86
30	16660122	1266503	66007	0,1	0,9
31	16660123	1266503	66010	0,1	0,7
32	16540050	1354213	51069	0,8	0,34
33	18540114	1354213	51069	0,8	0,86
34	18540115	1354213	51069	0,8	0,7
35	18540114	1354318	54007	0,3	0,84
36	18540065	1354404	51061	0,8	0,7
37	18540056	1354405	51021	0,8	0,68
38	17540082	1354408	54014	0,5	0,9
39	14210058	1421223	21075	0,8	0,5
40	17210156	1421227	21057	0,8	0,5
41	17210190	1421412	21007	0,8	0,5
42	17210110	1421500	21010	0,9	0,5
43	18220066	1422233	20002	0,5	0,9

Figure 4. Data normalization results

This data will then be used as processing data and training data that will be entered into the RapidMiner application. The determination of attributes and data classes is done by division as in the table below.

Table 1. Table of ikm attribute distribution

Number	Ikm	Value	Class
1	1	1	5
2	1	2	4
3	1	3	3
4	1	4	2
5	1	5	1
6	2	1	2
7	2	2	1
8	2	3	2
9	2	4	3
10	2	5	4
11	3	1	3
12	3	2	2
13	3	3	1
14	3	4	2
15	3	5	3
16	4	1	4
17	4	2	3
18	4	3	2
19	4	4	1
20	4	5	2
21	5	1	5
22	5	2	4
23	5	3	3
24	5	4	2
25	5	5	1

System formation, learning and testing processes are shown in figure 6 below

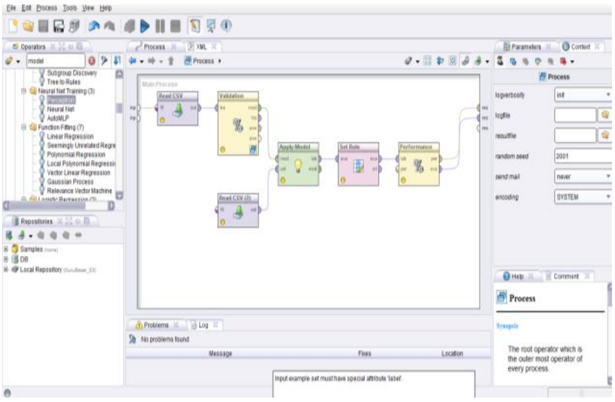

Figure 5. Establishment of the learning and testing process

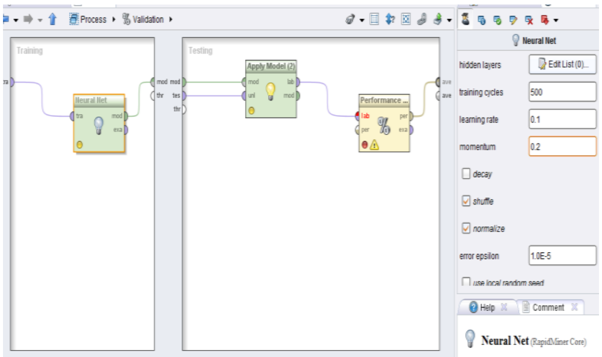

Figure 6. Backpropagation architecture on X-Validation operator

The parameters used in the backpropagation architecture to solve the above problem are:

Input	: 4
Training cycles	: 500
Learning rate	: 0.1
Momentum	: 0.2
Output	: 1
Error target	: 0.0001
Hidden	: 1 layer, 2 layer
Hidden 1 layer	: 2, 5, 8 neuron
Hidden 1 layer	: 2-5, 5-8 neuron

The above model is trained to choose the best architectural model as measured by the Root Mean Square Error (RMSE) parameter. The backpropagation model in the RapidMiner application can be created by clicking on the neural network (Figure 5.10) and selecting hidden layers in the parameters. The results of the implementation of the above model are as in Table 2 below:

Table 2. Root Mean Square Error (RMSE) training results with the Backpropagation algorithm

No	Model	RMSE
1	4-2-1	0.025 +/- 0.000
2	4-5-1	0.028 +/- 0.000
3	4-8-1	0.026 +/- 0.000
4	4-2-5-1	0.024 +/- 0.000
5	4-5-8-1	0.025 +/- 0.000

The results of processing using the RapidMiner application show that the backpropagation algorithm with the 4-5-1 model produces RMSE 0.028 with class division as Table 5.4 has the suitability of being the optimal model in measurement. In the class division, it also appears that the class with a. It's just that it should be noted that the RMSE value depends on the number of variables and the data that is processed. The more variables that are processed, the higher the value and the better model will also change. The result of a strong class status is more than any other status. This result is in accordance with the correlation approach. It's just that this classification also does not make the measurement of the value of the influence approach between variables visible in the classification. Another measurement method is needed that allows to measure the influence between variables.

4. CONCLUTION

From the research on the suitability analysis of the student satisfaction index with the value of the course using the significance correlation approach and backpropagation, the following results were obtained:

1. The results of the correlation measurement using the Pearson's correlation method produce a correlation value of r = 0.748 which means that the close relationship between the two variables is 0.748 or 74.8%.
2. The results of the correlation measurement using the coefficient of determination method produce a value of the coefficient of determination r2 = 0.559504. This means that the variable mk_value affects the result_ikm variable by 0.559504 or 55.9504%. This also means that there are 44.0496% factors from other variables that affect the measurement.
3. The results of the correlation measurement using the Pearson's correlation method yielded a significance value of t = 271.4732. This shows that the level of confidence in the measurement of the two variables above is very high.
4. The use of artificial neural network classification using the backpropagation algorithm with the help of the RapidMiner application to obtain optimal results of data processing using a 4-5-1 model with RMSE 0.0028 and classification with data classes according to the specified model. The class with strong status becomes the class that appears a lot in data processing.

From this research, it is hoped that further research will be carried out to determine other variables that influence the measurement of lecturer service satisfaction to students at State Islamic University of Maulana Malik Ibrahim Malang with the IKM Online application with student respondents. This determination is to test whether the instruments used for measurement in this pandemic condition are still reliable or whether improvements need to be made in describing the 4 competencies measured in the survey or need to be replaced. Evaluation and improvement in this measurement is expected to be able to provide an overview of service satisfaction from lecturers to students in learning to be closer to the truth.

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