Inverse kinematic solution of 6-DOF industrial robot using nero-fuzzy technology

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Abstract: The robot inverse kinematic controller does not give the shut frame arrangement. Henceforth Mechanical controller can accomplish end effectors position in more than one arrangement. To accomplish correct arrangement of the joint angle has been the fundamental worried in the research work. In this paper the analytical solution has been done using D-H method. The method gives 6 DOF industrial robot with D-H Parameter value, which will be the best uses for any inverse kinematics algorithm. Levenberg-Marquardt algorithm is used to solve inverse kinematic of 6-DOF industrial robot arm and the result has been simulated with different soft computing method like ANN and fuzzy logic. A comparison is taken between both the result obtain from different sources.

Keywords: inverse kinematics; ANN; fuzzy logic; industrial robot; forward kinematics; D-H parameters.

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1 Introduction

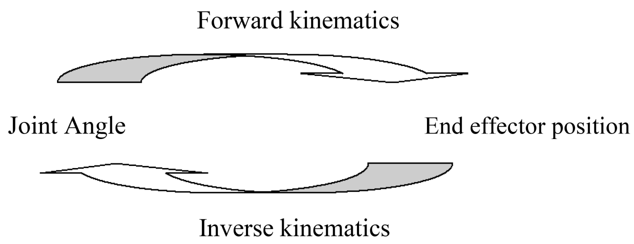
The robot manipulator is made out a consecutive chain of unbending connections associated with one other by rotational or prismatic joints. Every robot joint area is more often than are not characterised with respect to neighbouring joint. The connection involving progressive joints is depicted by 4 × 4 homogeneous change frameworks that have introduction and position information of robots. This numbers of changes frameworks decides the degree of flexibility of robot. In forward kinematics the end-effecter's area in the Cartesian position, that is its location and introduction, which is resolved in view of the joint factors.

The joint factors are the points among the connections, on account of rotational joints, or the connection augmentation, on account of kaleidoscopic joints. Alternately, specified end-effecter location and introduction, the backwards kinematics issue alludes to discover the estimations of the joint factors that enable the controller to achieve the specified area. The connections are amongst forward and backwards kinematics, and in addition the connection among joint location and Cartesian location. Tackling the reverse kinematics issue for mechanical controllers is a troublesome and furthermore very difficult assignment. The intricacy of this issue is specified by the robot's configuration and the nonlinear geometric conditions that portray the map among the Cartesian position and the joint position

$$\Theta = f^{-}(q)$$

where θ is represent the joint angle and q represented as end effectors position of the six degree of freedom robot.

Figure 1 Architecture kinematics



In spite of the fact that a shut frame for this issue is best in numerous applications, more often than not this is difficult to discover. Different approaches to decide the answer for the Inverse kinematics issue are anticipated. Their capacity to be trained by case makes them a decent possibility to give the map among the Cartesian position and the joint position vital by the reverse kinematics issue. In a few neural system structures utilised for tackling the opposite kinematics issue are broke down. These incorporate back spread prepared bolster neural systems whose weights are characterised as far as transgression and cosine to fit the forward kinematics portrayal of the robot.

The article researches the utilisation of a neuron system to deliver the answer for the inverse kinematics issue for the six link automated controller. The neural architecture are utilising the information gave by the presumptuous kinematics to take in the backwards forward map of the arrangement position. It implies the end effecter's place and introduction are given as information sources and the neural system recognises which joint arrangement compares to the given restriction.

2 Related work

El-Sherbiny et al. (2017) developed a virtual learning of soft computing technique for solving inverse kinematics problem. The work used that different soft computing method like ANN and ANFIS to minimise the error function of an inverse kinematics of a five DOF robot. The accuracy is improved for both ANN and ANFIS after using MEF. The work concluded that after using MEF, the accuracy value increased but still ANN is acceptable by many industry for IK calculation. Di Vito et al. (2017) entitled an essential re-evaluate of the inverse kinematics algorithms of robots in existence of kinematic singularity. The attainments a singular arrangement by an error unlike from zero usually affect the effectiveness of numerous algorithms. The none of algorithm takes into account real time. The Baerlocher's algorithm was the most useful one. Kalra et al. (2012) presented a developmental approach in light of a genuine coded hereditary calculation, which is utilised to acquire the arrangement of the seven DOF backwards kinematics arrangements of modern robots. All the various arrangements acquired by this advance can be shown utilising a 3D modeller created in MATLAB with the end goal of perception. Denkenaa and Lepper (2015) developed a commercial developed of enormous structure parts for aerospace industries with an industrial robot. This work is to optimise the position of robot by return of tool variation. By taking static variation caused by forces acting on the spindle, a model of the robot is built up. Kucuk and Bingul (2014) developed the solution of Inverse kinematics for industrial robot manipulators through offset wrists. Out of different analytical method new inverse kinematic algorithm and Newton-Raphson method used in the paper for inverse kinematic solution of 16 industrial 6 DOF industrial robots. The solution it gives closed form solution. Raza et al. (2018) presented a kinematic study and geometrical enhancement of an industrial robot. Here Robo-analyser is used for optimal location and orientation of required robot arm and the arm structural analysis is done. In this exploration, centre is to examine the achievability of coordinating apparatuses from different spaces, for example, Parametric CAD displaying and FEA, which gives an idea to the industrialist how to get an ideal arm configuration to build their generation rate and so on. Duka (2014) approached a neural system-based backwards kinematics answer for direction following of an automated arm. The feed forward network is used to solve the three link kinematic manipulator. The informational indexes, utilised for preparing the neural system, are resolved dependent on the forward kinematics conditions of the robot and the neural system is prepared to take care of a reversal issue, creating the information sources that match the yields. The two-layer feed-forward system with sigmoid concealed neurons and direct yield neurons can fit multi-dimensional mapping issues. Some few headings that require promote consideration to calculation to genuine mechanical controllers. Nicolato and Madrid (2005) used recursive algorithm to solve inverse kinematic by allowing one joint to move at a time also D-H method used for analytical solution. A recursive technique for illuminating the opposite kinematics of excess robots was exhibited in this paper. As can be seen from the outcomes, the proposed technique can productively adapt to join position and speed limits. This reality prompts the likelihood of forcing a coveted conduct for the robot, as it is appeared in the repeatability model. Additionally, because of the normality and effortlessness of its tasks, the proposed technique can be effectively executed progressively by methods for computerised flag processors. Perrusqu et al. (2017) developed a stable admittance control without inverse kinematics. The admittance control is use the orientation of end effectors to create required joint angle to avoid inverse kinematics solution. In this paper, novel permission controller are displayed which work in joint space and need not bother with the reverse kinematics of the robot. These PD controllers also use adaptive and sliding mode compensations to improve the tracking accuracy. Stability of the controller is popover analysis. The proposed controllers are verified using a 2-DOF pan and tilt robot and a 4-DOF skeleton with F/T sensor. The comparisons between traditional and proposed controllers are made. The controllers do not require inverse kinematics or Jacobian parameters , they only use the orientation components. Santolaria and Gine (2013) presented a paper improbability evaluation in robot kinematic calibration. The circle point analysis method adopted for calibration improbability of robot arm. The best data set is capture for robot kinematic accuracy. Findeisen (2018) presented a technique for energetic assessment of six-axis industrial robots and its further possibility for resource-effective plant design. The technique portrayed in this work, which has been created for this particular reason, can be exchanged and reached out to other complex gathering and assembling frameworks even with fluctuating arrangement situations. Subsequently a cross industrial advantage for ideal vivacious task of modern assembling frameworks can be accomplished. Hamaya et al. (2017) presented learning assistive strategies for exoskeleton robots from user-robot physical interaction. To formulate the learn issue of assistive procedures as a strategy look issue and endeavour an information effective model-based fortification learning system. Rather than obviously giving the coveted directions in the cost work just considers the client's solid exertion estimated by electro Murphy signals (EMGs) to take in the assistive methodologies. The key basic suspicion is that the client is told to play out the errand by his/her own planned developments. Since the EMGs are watched when the planned developments are accomplished by the client's own muscle exertion s as opposed to the robot's help, EMGs can be deciphered as the "cost "of the present help. Wei et al. (2014) developed common approach for inverse kinematics of NR robots. The article utilises a semi-scientific technique and a common strategy to tackle the spatial NR robot opposite kinematics issue. These defeats the arithmetical strategy's restrictions identified with exactness with a continuous angle. At first conformal geometric location hypothesis is utilised to build up common kinematic conditions. The weighted space vector projection strategy is utilised to dissect the connection among the robot spatial turn points and the estimation of the location vector projection. The weighted estimation of all joint projection on the end-effectors vector is dealt with as the reason for changing the robot end's introduction. Di Vito et al. (2017) review an assessment of damped least squares algorithms for inverse kinematics of robot manipulators. In this work specifically, with the mean to survey the effectiveness in taking care of joint speed limits and the likelihood that the objective esteem is actually not reachable. Ongoing control of repetitive robot driven by administrator cannot ensure, truth is told, that they chose target compares to a non-solitary arrangement. Then again an acting the regularisation factor too a long way from the peculiarity relates to extensive following blunders and serious speed imperatives. What's more, as it will be appeared in the work, achieving a particular arrangement with a blunder not the same as zero as a rule influences the effectiveness of a few calculations. Iliukhin et al. (2017) presented the modelling of Inverse Kinematics for 5 DOF manipulators. This work is the piece of research went for making mechanical controller controlled by methods for Brain-Computer Interface for enhancing family unit confidence of people with incapacities and extending the extent of their activity. The automated controller gives probability of self-satisfaction in essential family works drinking, eating, facial cleanliness. Sardana et al. (2013) represent a statistical approach for inverse kinematics of a 4-link redundant in-vivo robot for biopsy. This paper introduces a basic geometric come near, to tackle the issue of different backwards kinematic arrangements of repetitive controllers, to locate a solitary ideal arrangement and to effortlessly change starting with one arrangement then onto the next relying on the way and the earth. A recreation representation of the approach has been created and tests have been led on the in-vivo robot to judge its viability. Sugiarto and Conradt (2017) purposed model-based advance to robot kinematics where discrete belief propagation is used to control. The paper describes the improvement of a non specific strategy in view of factor diagrams to show robot kinematics. Here the concentrated on the kinematics part of robot manage since it gives a quick and deliberate answer for the robot specialist to move in a dynamic situation. The authors grew neurally-roused factor diagram models that can be connected on two distinctive automated frameworks a portable stage and a mechanical arm. Similarly it shows that any can broaden the static model of the automated arm into a dynamic model valuable for mirroring characteristic developments of a human hand. Reinhart and Steil (2016) purposed a paper hybrid mechanical and data-driven modelling improves inverse kinematic control of a soft robot. The work demonstrates that feed-forward control in view of reversal of a half and half forward model containing a mechanical model and an educated blunder model can essentially enhance precision. The projected approach is exhibited for backwards kinematic control of an excess delicate robot with a mixture demonstrate that is built from variety kinematics together with an effective neural system blunder show. Köker (2013) purposed a hereditary calculation way to deal with a neural-arrange-based backwards kinematics arrangement of mechanical controllers in light of mistake minimisation. In neural system and hereditary calculations are utilised together to take care of the converse kinematics issue of a six-joints. Stanford automated controller to limit the blunder toward the end effectors. The proposed work joins the qualities of neural systems and transformative procedures to obtain more exact arrangements. Three Elman neural systems were prepared utilising separate preparing sets since one of the sets yield preferable outcomes over the other two. The gliding point parts of all system were set in the underlying populace of the hereditary calculation through the coasting point divides from arbitrarily produced arrangements. The end-effectors position blunder is characterised as the wellness work and the hereditary calculation was executed. Utilising this approach, the drifting point bit of the neural-arrange result is enhanced by up to ten noteworthy digits utilising a hereditary calculation, and the mistake was decreased to micrometer levels. Kalra (2006) purposed a developmental approach for taking care of the multimodal converse kinematics issue of mechanical robots. The converse kinematics arrangement of a modern robot may give various robot setups that all accomplish the required objective position of the controller. Without deterrents, variety determination can be accomplished by choosing the robot design nearest to the present robot setup in the joint space. A transformative approach in view of a genuine coded hereditary calculation is utilised to get the arrangement of the multimodal reverse kinematics issue of modern robots. All the numerous designs got by this approach can be shown utilising a 3D modeller created in MATLAB with the end goal of representation.

2.1 Back ground of the work

In this exploration work, genuine neural system connected for the arrangement of reverse kinematics of 6 DOF controllers. The strategies are in multilayer perceptions and polynomial pre-processor neural system has connected. The main goal of the work is to be anticipate the estimations of joint points (reverse kinematics), as it is understand that there is no one of a kind answer for the converse kinematics even scientific formula are mind boggling and time taking so it is smarter to discover arrangement through neural system.

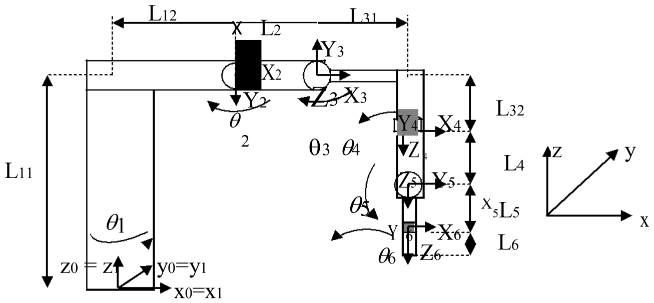
3 Problem statement

The kinematic chain comprises of kinematic match by connections, which might be associated by revolute or kaleidoscopic joints subjected to rotating or translational level of opportunity. It clarified that numerous methodologies are available to solve the numerical portrayal of kinematic chain. The real contrasts of these techniques are the connection of facilitate outlines. In this manner Denavit-Hartenberg parameters are generally utilised. The strategy comprises of 4 scalars 98.99, are known as D-H parameters of kinematic chain. The scalars are utilised to characterise the geometry of connection and next of kin uprooting of the joint. This strategy for portrayals decreases the scientific/arithmetical tasks for the kinematic depiction.

Scientific methodologies are more confounded according to arithmetical, iterative or savvy-based techniques. The acquired arrangements utilising these strategies are setup reliant as well as issues to uncertainty of the assembling blunders. Subsequently, to conquer scientific intricacy and enhance the proficiency of the arrangement, it is important to embrace designing streamlining strategies. Enhancement strategies can be connected to explain backwards kinematics of controllers as well as general spatial system. Fundamental numerical methodologies i.e., Newton-Raphson strategy can illuminate nonlinear kinematic formulae or an additional advance is indicator corrector type techniques to absorb discrepancy kinematics formulae. Along these lines enhancement-based calculations are very productive to tackle reverse kinematic issue. For the most part these methodologies are more steady and regularly focalise to worldwide ideal indicate due minimisation issue.

To work out the joint position for a specified rest of end effectors coordinates is called inverse kinematics. The equations are in common, nonlinear and complex so inverse kinematics analysis reasonably difficult. Figure 2 represent the six degree of freedom manipulator.

Figure 2 The structure of 6 DOF manipulator



The model represents the B homogeneous transformation matrix which uses four link parameters.

$$B = Rot(z, \theta)trans(0, 0, d)trans(a, 0, 0)Rot(x, \alpha)$$

where 'θ' is the joint angle, 'd' is the joint off set, 'a' is the link length ,and 'α' is the link twist

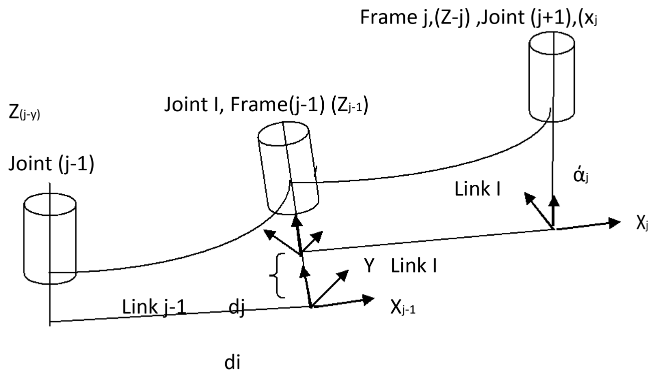
$$T_6 = B_1 B_2 B_3 B_4 B_5 B_6$$

3.1 D-H parameters

It gives us a chance to watch every single trademark property of the scalar parameter of D-H technique for demonstrating of measured kinematic combine in Figure 2. Standard technique for portrayal has been taken after without adjusting the worry properties of kinematic match.

From Figure 2, connection $j - 1$ associated by barrel shaped joint with interface j, and $j + 1$ interface is successive connection with same joint I. The appended organise outline with connect j is orientated such that the Z_j pivot is lined up with sequential connection $j + 1$ and X_j-hub is lined up with regular ordinary in the middle of j and $j + 1$. Base organise outline is arranged at the convergence of regular typical with $j + 1$ pivot. What's more, the last arrange Y_j will be set according to right hand administer which is $y_j = z_j + x$.

Figure 3 D-H architecture



To get the immediate kinematics of a robot controller, one ought to characterise the homogeneous change grid for each joint. Utilising DH parameters, the homogeneous change lattice for a solitary joint is communicated as

$$_{j}^{j-1}T = \left|\sin\theta_j\right| \begin{bmatrix} \cos\theta_j & -\sin\theta_j & 0 & a_{j-1} \\ \cos\theta_{j-1} & \cos\theta_j\cos\theta_{j-1} & -\sin\alpha_{j-1} & -\sin\alpha_{j-1}d_j \\ \sin\theta_j\sin\theta_{j-1} & \cos\theta_{j-1} & \cos\alpha_{j-1} & \cos\alpha_{j-1}d_i \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

where there is the point amongst $x_j - 1$ and x_i to Mohawks estimated about z_j hub, α_i is the edge amongst z_j and $z_j - 1$ to Mohawks estimated about x_j hub, α_j is the separation from z_j to $z_j - 1$ tomahawks estimated along x_j pivot and d_j is the separation from $x_j - 1$ to x_i tomahawks estimated along z_j pivot. The forward kinematics of the end-effector regarding the base edge is gotten by increasing the majority of the $_{j}^{j-1}T$ *j*-1jT matrices.

$$\begin{matrix} _{b}^{p}T = n & s & a & p \\ 0 & 0 & 0 & 1 \end{matrix} \quad (1)$$

where, is the typical vectors is the sliding vector, a is the moving toward vector and p is the position vector. Utilising equation 1, one can decide the position and introduction of the end-effector as far as the joint variables.

Table 1 D-H parameters

Joints	*Θ_i(degree)*	*d_i(m)*	*a_i(m)*	*α_i (degree)*
0	+160 to –160	0	0	92
1	–220 to +55	0	0	0
2	–55 to +220	0.224	0.386	–90
3	+120 to –120	0.560	0.045	90
4	+100 to –100	0	0	–95
5	–260 to +260	0	0	0

4 Numerical solution technique

An effective calculation ought to have following highlights:

1 it diminishes the opposite kinematics calculation time

2 it limits position error between wanted and last position

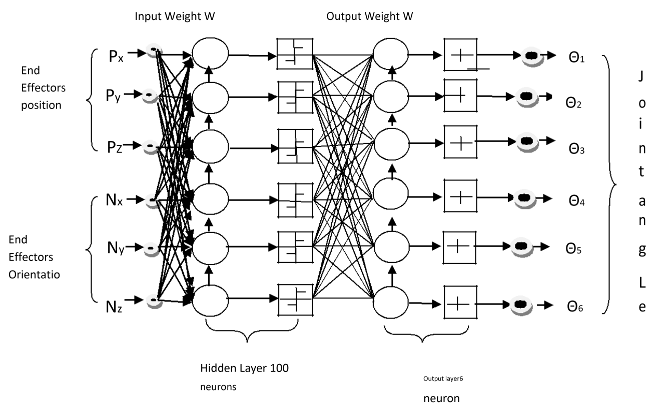
3 it controls merging of arrangement vector to right points.

It can figure joint factors not as much as a couple of milliseconds with under 0.0001 position blunders.

5 The neural network

The artificial neural system (ANS) especially MLP neural system is for the most part used to learn forward and in addition reverse kinematics condition of different arrangement of the controller. This technique depends on learn procedure of some model information which depend on the space of the controller or component. In the event of ANN there are numerous methods for learning information, for example, directed learn, unsubstantiated or blend of both. ANN takes after the useful connection between the info factors (Cartesian facilitates) and yield factors (joint directions) in view of the nearby update of mapping amongst information and yield. This idea is likewise a reason for fluffy rationale and cross breed astute strategies which prompts basic arrangement of reverse kinematic dropping the regular complex numerical formulae. The re-enactment and calculation of opposite kinematics utilising shrewd procedures are prevalently helpful where less calculation cost is required, unquestionably to control progressively condition. In the event that the setup of controller and also considering number of DOF expands, at that point the customary logical strategies will transform into more mind boggling and troublesome science. There are various research has been done in the field of ANN, fluffy rationale and furthermore for cross breed systems. The feed-forward neuron network is anticipated to work out the solution of inverse kinematics problem. To get trained data for the neural network, arbitrary joints angle value that consistently face the ranges particular in equation (2) are general.

Figure 4 Architecture of multi layer neural network



The neural network is running with regression mode so the input and output neuron are one to one. The above feed forward neural system comprises of 6 inputs, 100 neuron in the shrouded layer and 6 neurons in yield layer. The exchange work for the neurons in the shrouded layer is the hyperbolic digression sigmoid, appeared in condition and the yield neurons is the straight capacity, appeared

$$y = \tanh(x) = \frac{e_{2x} - 1}{e_{2x} + 1} \quad (2)$$

The required yield of the neural system speaks to 6 in 1 vector of joint angles consequent to the six joints of the robotic arm. The calculated value is depends upon on the required location and orientation of the end-effecter as per given to equation.

$$\begin{pmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \\ \theta_4 \\ \theta_5 \\ \theta_5 \end{pmatrix} = w \tanh_o \left| wi \begin{pmatrix} P_x \\ p_y \\ P_z \\ N^z \\ N^x \\ N^Y \\ N_z \end{pmatrix} + B_i + \begin{pmatrix} b_{o1} \\ b_{o2} \\ b_{o3} \\ b_{o4} \\ b_{o5} \\ b_{o6} \end{pmatrix} \right. \quad (3)$$

In the above equation W is 100 by 6 matrix carries weights and hidden layer. B_i represent is the bias for the hidden layer.

The Levenberg-Marquardt calculation, otherwise called the damped minimum squares strategy, is intended to work particularly with misfortune capacities which appear as a total of square blunders. It is working without figuring the correct Hessian matrix. Rather, it works with the slope vector and the Jacobian matrix.

Consider a misfortune work which can be communicated as a total of squared blunders of the

$$\text{for} \quad f = \sum\nolimits_{e_i}^{2} i = 0 \ldots n \quad (4)$$

where n is the quantity of cases in the informational index.

The Jacobian matrix can be used as lose function which contain the derivative of the blunders as for the parameters

$$J_{ij} f(w) = de_i / dw_j \quad (i = 1 \ldots p \quad \text{and} \quad j = 1 \ldots q) \quad (5)$$

P is representing the number of instance data sets and q is the number of parameters in the neural network.

The loss function can be compute as $\forall f = 2^t.e$ (6)

where e is representing the vector error.

$$hf \approx 2j^t \cdot j + \lambda i \quad (7)$$

where λ is a damping factor that guarantees the inspiration of the Hessian and I is the character framework. The following articulation characterises the parameters change process with the Levenberg-Marquardt calculation.

$$w_{i+1} = w_i - \left[j_i^t \cdot j_i + \lambda_i I \right)^{-1} \cdot \left(2 j_i t \cdot e_i \right) \quad i = 0, 1 \ldots$$

At the point when the damping parameter λ is zero, this is only Newton's strategy, utilising the inexact Hessian framework. Then again, when λ is huge, this moves toward becoming angle plummet with a little preparing rate. The parameter λ is introduced to be expansive with the goal that first updates are little strides in the slope plummet heading. In the event that any emphasis happens to bring about a disappointment, at that point λ is expanded by some factor. Something else, as the misfortune diminishes, λ is diminished, with the goal that the Levenberg-Marquardt calculation approaches the Newton strategy. This procedure regularly quickens the union to the base the Levenberg-Marquardt calculation is a strategy custom fitted for elements of the sort whole of-squared-mistake. That makes it to be quick when preparing neural systems estimated on that sort of blunders. In any case, this calculation has a few disadvantages. The first is that it cannot be connected to capacities, for example, the root mean squared blunder or the cross entropy mistake. Additionally, it is not perfect with regularisation terms. At long last, for huge informational collections and neural systems, the Jacobian lattice ends up gigantic, and thusly it requires a ton of memory. Consequently, the Levenberg-Marquardt calculation is not suggested when we have enormous informational collections as well as neural systems.

5.1 *Proposed nero-fuzzy method*

Neuro-fuzzy inference frameworks have been created to combine data handling ability of fuzzy inference systems and learning ability of neural systems for illuminating frameworks. Neuro-fuzzy inference system technique for understanding opposite kinematic issue utilises an arrangement of information for preparing the framework which will be utilised later to locate the joint points θ_1 by a given Cartesian area X, Y and Z and the introduction points N_x, N_y and N_z. This set of information must cover the entire workspace of the robot to be capable to give the answer for any point in the Cartesian area which robot end effector can reach. So we can utilise a similar arrangement of information utilised before with neural system preparing. As neuro-fuzzy inference is a multi input single yield framework, the proposed framework is made out of five neuro-fuzzy inference frameworks. Presently we have six unique frameworks each for one of the yields (joint points).

6 Result and discussion

With the fundamental inverse kinematic equations and considering different position and orientation of the 6-DOF Aristo Industrial robot the different joint angles are calculated, which is shown in Table 2.

Table 2 End effectors position and orientation vs. joint angle

P_x	P_y	P_z	N_x	N_y	N_z	Θ_1	Θ_2	Θ_3	Θ_4	Θ_5	Θ_6
0.30	378.88	393.84	–90	0.02	176.72	90	–89.9	90	0	90	0
2.29	281.47	394.37	95.1	1.32	176	89.85	89.82	89.28	3.25	88.5	4.68
29.85	414.98	336.66	–130	1.80	150.23	82.39	–85.5	95.44	26.55	63.93	24.37
49.00	419.98	288.56	–136.9	–9.61	153.7	79.51	–80.4	97.11	29.02	67.05	28.57
0.52	395.1	351.4	–118.7	–3.72	157.08	86.45	–87.8	95.02	22.92	76.98	21.74
–8.11	390.57	375.52	–109.4	1.83	161.75	88.51	–89.2	92.5	17.17	79.71	15.46
–02.5	383.3	382.24	–98.8	2.44	174.45	89.56	–89.9	89.8	4.55	89.11	5.58
–02.4	380.14	394.7	–96.08	0.56	175.47	89.65	–89.9	89.87	4.55	89.12	5.58

6.1 *Validation of result using ANN tool*

The best experimental data set are used in Multilayer neural network tool and left for continuous training. It gives Performance curve and regression curve which is shown in Figure 5 and Figure 6. The training value, validation value and testing value curve are parallel to each other with very less mean square error of 0.4 only. Similarly the regression curve gives the relation between the dependent variable (target value) and independent variable (output value). All the curve shows linear curve and the target values are varying near by the liner curve.

Figure 5 Performance curve (see online version for colours)

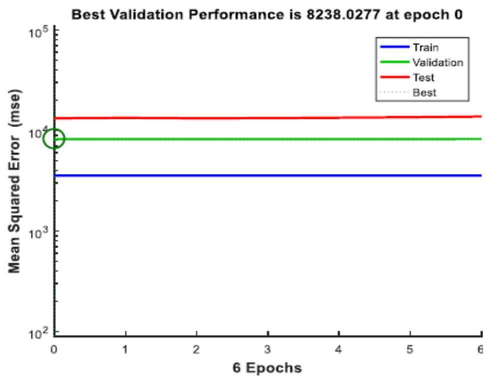
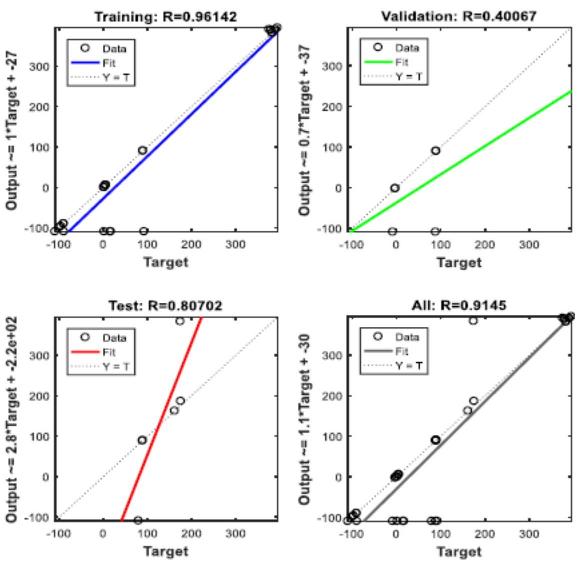


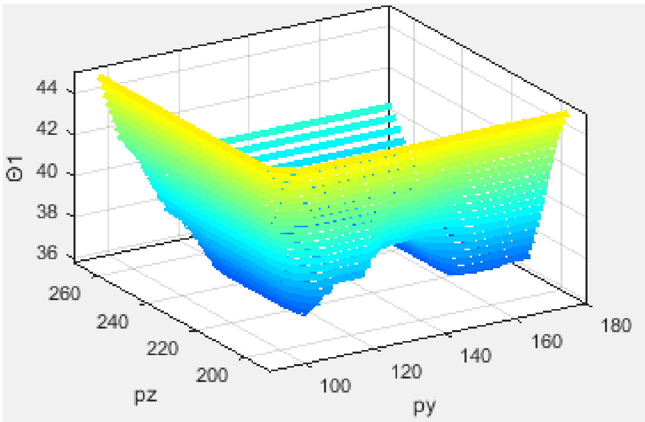
Figure 6 Regression curve (see online version for colours)



6.2 *Joint angle position with respect to end effectors position using fuzzy logy*

Figure 8 represents the joint angle value with respect to end effectors orientation. In Figure 7 P_y value varies from 90° to 190° accordingly the joint angle (θ_1) comes in between 35° to 95°. Figure 8 indicates the joint angle variation with respect to end effectors position P_x and P_z.

Figure 7 θ_1 position with respect to end effectors position in x and y direction (see online version for colours)



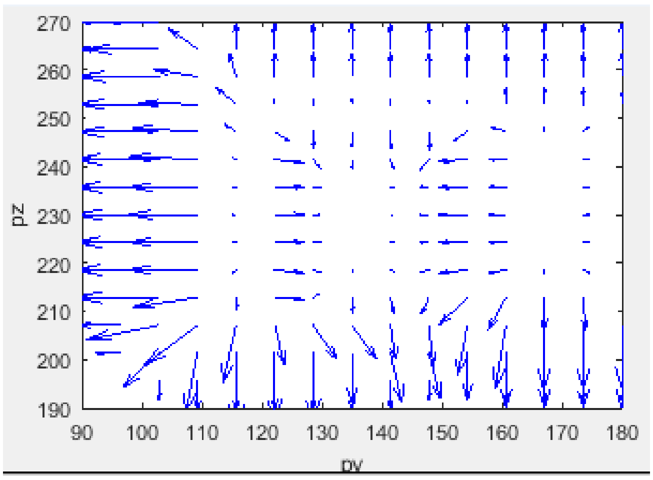


Figure 9 shows the joint angle position with respect to end effector orientation value. With the simulation of fuzzy logic the optimum value of joint angle one is 44.2° which is nearly equal to the experimental average vale.

Figure 8 θ_1 position with respect to end effectors position in *x* and *z* direction (see online version for colours)

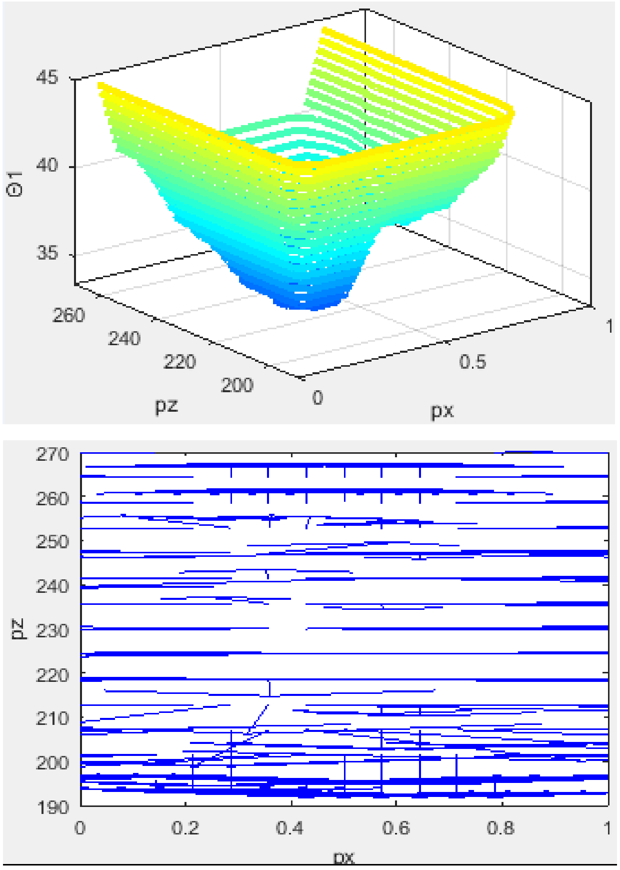


Figure 9 θ_1 position with respect to end effectors orientation x and y direction (see online version for colours)

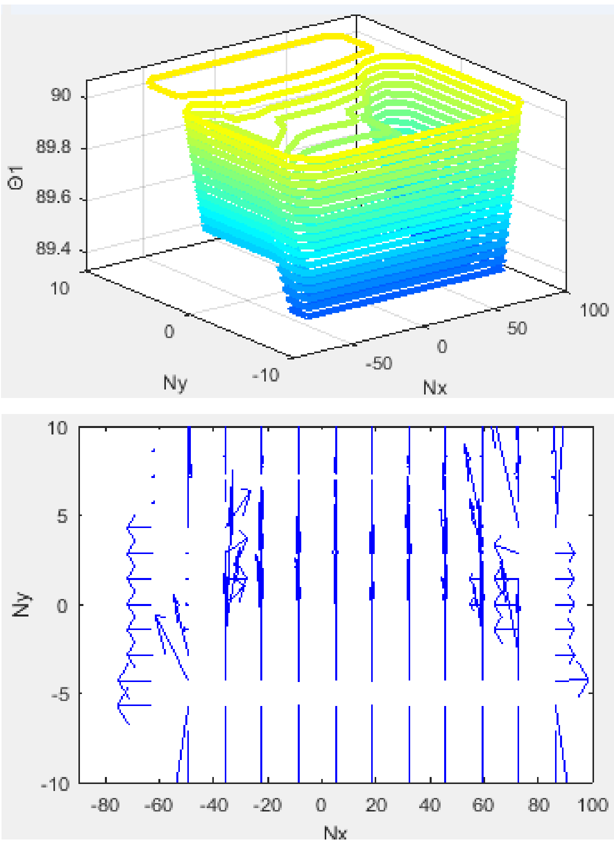


Figure 10 θ_1 position with respect to end effectors orientation *x* and *z* direction (see online version for colours)

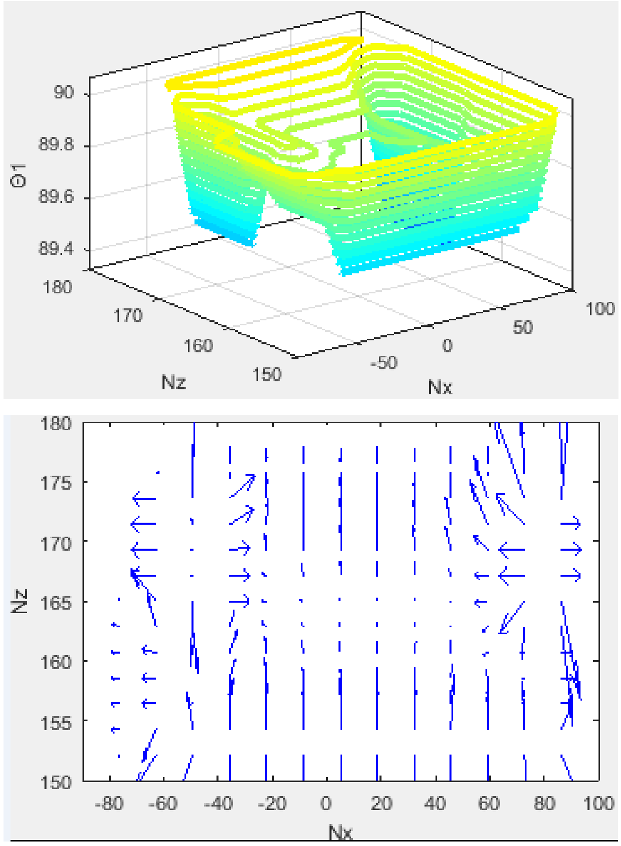
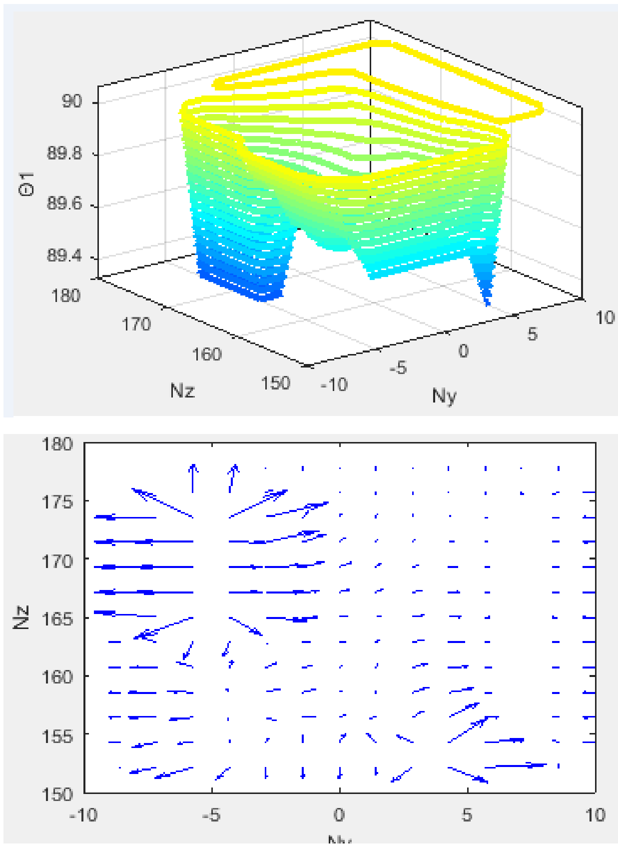


Figure 11 θ_1 position with respect to end effectors orientation y and z direction (see online version for colours)



Similar anticipation is done in Figure 10 by taking different orientation value that Nx and Nz where joint angle value one is nearly equal.

Figure 11 shows that angle position of joint angle one with respect to the variable end effectors orientation value N_y and N_z.

7 Conclusions

This work represents the best validation of data set in ANN tool and fuzzy logic. In Neural Network tool data set are trained with an error of 0.4% and its all joint angle values are nearly matching with the experimental value. The best variation of joint angle with respect to end effectors orientation is obtained with fuzzy logic Simulink. With an average value of $P_x = 0.789$, $P_y = 130$ and $P_z = 215$, the joint angle of first joint reached 40.8°. Similarly by considering the average orientation value i.e., N_x, N_y and N_z the values of joint angle reach 41.08°. So it concluded that simulation value changes slightly in end effectors position value and orientation value. The similar simulation has been done for the joint angle like θ_2, θ_3, θ_4, θ_5 and θ_6 and the achieved values are nearly equal to its target value.

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