

## Chapter 45

# Optimal Model Parameters of Inverse Kinematics Solution of a 3R Robotic Manipulator Using ANN Models

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### **ABSTRACT**

*Solution of inverse kinematics equations of robotic manipulators constitutes usually a demanding problem, which is also required to be resolved in a time-efficient way to be appropriate for actual industrial applications. During the last few decades, soft computing models such as Artificial Neural Networks (ANN) models were employed for the inverse kinematics problem and are considered nowadays as a viable alternative method to other analytical and numerical methods. In the current paper, the solution of inverse kinematics equations of a planar 3R robotic manipulator using ANN models is presented, an investigation concerning optimum values of ANN model parameters, namely input data sample size, network architecture and training algorithm is conducted and conclusions concerning models performance in these cases are drawn.*

## **1. INTRODUCTION**

Industrial production became highly automated from early 1900s and on. The assembly line of early automotive industries can be considered as the earliest form of automated systems in manufacturing industry. Automated systems have resulted in increased productivity, improved product quality and accurate manufacturing, lower production costs and significant reduction in production time. Furthermore, these systems are widely employed not only for monotonous or repetitive tasks but also in harsh and hostile environments or in cases when significant amount of force or other capabilities are required that man is impossible to provide. However, the design and development of automated systems requires significant research work and financial costs in order to ensure safety in the workplace and high quality of final products. Nowadays, automation components of various types are present in industrial production lines such as computer systems, employed in many stages from design to control of production line, robotic systems, used for several tasks such as welding or assembling processes, as well as other minor electronic automations.

Especially, industrial robots were first employed in the 1960's, in automotive industry (Shell and Hall, 2000). ISO 8373 (1994) defines an industrial robot as an automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes. Some of mostly employed robot types are SCARA (Selective Compliance Articulated Robot Arm) robots, articulated robots and Cartesian coordinate robots. Early industrial robots were employed only to transfer various objects between different positions but nowadays they perform considerably more complicated tasks such as assembling, product inspecting, painting etc. Apart from the programming and controlling of robotic systems, the first and most fundamental analysis stage is the kinematics analysis.

Kinematics analysis is essential in order to plan the conduction of tasks efficiently and also in order to ensure the safe use of these robotic systems. Kinematics analysis is divided in two major categories: Forward kinematics and Inverse kinematics. Forward kinematics are used to compute the configuration of the robot, given its geometric parameters and inverse kinematics are employed to compute the opposite problem, which is a more laborious and complicated task. Several methods have been developed to deal with these two problems, with various shortcomings.

During the last few decades, the use of advanced methods such as soft computing has been introduced in robotic systems kinematics analysis as alternative methods with considerable potential improvement. Artificial neural networks (ANN) application in solving the inverse kinematics problem was first reported during the 1980s in works such as the work of Guez and Ahmad (1988). Hou and Utama (1992) were among the first to solve the inverse kinematics problem for a redundant manipulator using ANN. Wada and Kawato (1993) proposed a novel neural network model to calculate arm trajectory in order to overcome the deficiencies of previous models based on minimum torque-change criteria. Gupta et al. (1994) employed a neural network with dynamic neural units as computational nodes for the accurate prediction of end effector position and orientation. Tejomurtula and Kak (1999) presented solutions to inverse kinematics problem by employing various soft computing methods such as multilayer perceptrons (MLP), modified MLP and Kohonen maps. Karlik and Aydin (2000) compared the performance of two different ANN architectures concerning the prediction of motion of 6 degrees of freedom (DOF) robotic manipulator. Oyama et al. (2001) developed a novel module neural network model composed of individual expert networks. Furthermore, performance was measured in order to determine the number of expert networks and reduce computational time.

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