
Productivity improvement of an eco friendly warehouse using multi objective optimal robot trajectory planning

S. Mahalakshmi* and A. Arokiasamy

Department of Computer Science and Engineering,
E.G.S. Pillay Engineering College,
Nagapattinam, 611-002, Tamil Nadu, India
Email: s.mahalakshmi1983@gmail.com
Email: a.arokiasamy@gmail.com
*Corresponding author

J. Fakrudeen Ali Ahamed

Engineering Department,
Nizwa College of Technology,
P.O. Box 477, 611 Nizwa, Sultanate of Oman
Email: saffaa2002@gmail.com

Abstract: Production of environment is one of the top rated objectives of all countries. 10% emission of CO₂ in the world is from logistics industries due to freight transports and warehousing operations. Green logistics is an important step to minimise ecological impacts of the logistics operations. Green environment in a warehouse plays a mandatory role in green logistics. Automation, robotics and smart systems give a good contribution in making the warehouse environment clean and green. A method for productivity improvement of a green warehouse using multi objective optimal trajectory planning of a warehouse robot is proposed in this paper. Mixed load palletising operation (build-to-order palletising) is considered. Two multi objective optimisation algorithms such as multi objective particle swarm optimisation (MOPSO) and multi objective differential evolution (MODE) are used. A numerical example on an Industrial robot (MTAB ARISTO 6XT robot) is presented. An economic and productivity analysis is carried out. The obtained results proved that the multi objective optimisation on warehouse robot trajectory planning enhances supply chain productivity and profits.

Keywords: green supply chain; green logistics; productivity improvement; mixed load palletising; eco friendly warehouse robot; multi objectives; optimal trajectory planning; MOPSO; multi objective differential evolution; MODE.

Reference to this paper should be made as follows: Mahalakshmi, S., Arokiasamy, A. and Ahamed, J.F.A. (2019) 'Productivity improvement of an eco friendly warehouse using multi objective optimal robot trajectory planning', *Int. J. Productivity and Quality Management*, Vol. 27, No. 3, pp.305–328.

Biographical notes: S. Mahalakshmi received her MCA from the Alagappa University, Karaikudi. She received her ME in Computer Science and Engineering from the Anna University, Trichy. Currently she is doing her PhD in the Anna University, Chennai. Her research interests are robotics and intelligent optimisation techniques.

A. Arokiasamy received his ME in Computer Science and Engineering from the Bharadhidasan University, Trichy. Also he received his PhD from the Bharadhidasan University, Trichy. Currently he is working as a Professor in the Department of Computer Science and Engineering, E.G.S. Pillay Engineering College, Nagapattinam, Tamil Nadu, India. His research interests are computer graphics, electronics, microprocessor and robotics.

J. Fakrudeen Ali Ahamed received his BE in Mechanical Engineering from the Bharadhidasan University, Trichy. Also he received his ME in CAD/CAM from the Anna University, Chennai. Currently, he is working as a Faculty in the Engineering Department, Nizwa College of Technology, Oman. His research interests are CAD/CAM, optimisation techniques and robotics.

1 Introduction

At present, environment is one of main indicator in successful implementation of sustainable supply chain management. The value of a sustainable supply chain management is based on the balancing between environmental and economic efficiency.

Green logistics means eco-friendly environment and transportation system. It improves efficiency of distribution system. At present logistics industry are much concern about environment and very keen to find new systems. Warehouse management is a mandatory part of logistics. Due to environmental consideration, the objectives of logistics have been changed as reduction in cost, less energy consumption, less transport time, increased reliability, environment friendly transportation, reduce pollution, delivery on time, less waste, increase inventory turnover, e-commerce, etc. To fulfil these objectives, few intelligent techniques such as swarm intelligence (Zhang et al., 2015) and technologies are needed to green logistics.

The supply chain processes need to be enhanced with new technologies viz., artificial intelligence (AI), robotics and big data methods (Merlino and Sproge, 2017). Then only the supply chain will be suitable for ever growing technological and environmental changes. Further supply chain can be sustainable and fulfil consumers' demands.

Recently the consumer expectations are getting changed due to social media, TV, internet, teleshopping, e-commerce, online purchase and omni channel, etc. They have more options on price, selection, shopping experience and delivery methods. To meet and fulfil the consumer requirements, the nature and operational policies of supply chain have to be changed. The supply chain face challenges like sensitive market, supplier changes, new sales channels, new products and sales growth. The fulfilment operations and distribution works are very much affecting the supply chain (Chand et al., 2015). E-commerce sales increase pressure on retailers to increase the speed between click and delivery. For this, automation in retail warehouse and logistics operations is a vital one. Robotics is an essential and important technology for warehouse automation (Barreto et al., 2017).

At present, the robots are introduced in the supply chain. Warehouse robots are getting place in the logistics company. Recently Amazon, DHL and other leading industries in supply chain have added some robots in their warehouses. Due to which they are getting success and savings.

Few researchers demonstrated that usage of service robots (Karabegović et al., 2015), mobile robots (Yuan and Gong, 2016), cloud auction robot (Kong et al., 2017) and AGV

(Bechtsis et al., 2017) in logistics leads to performance improvement, labour reduction, high productivity, optimised manufacturing time and costs.

Usage of robots gives a possible solution to the day by day increasing pressure in the supply chain. Robots can help the supply chain in picking, material transport, sorting, material storage, material loading and unloading, order fulfilment and audits.

To meet the varying need of customers, an important concept in the warehouse is mixed load pallets. Mixed load pallets have mixture of different products. Mixed load pallets give benefits like savings in the floor space and inventory, reduction in labour, cost effective, increased efficiency, increased order accuracy, high uptime, high density pallet loads, increased capacity and flexibility, improved ergonomics, good safety, etc. Mixed load palletising is also called as build-to-order palletising method. In this method, the pallet has only the needy products of a particular customer or a retailer or a distributor. This also reduces the inventory costs of a retailer or a distributor. To implement mixed load pallet method, Stationary piece picking robots are the best choice.

Better material handling devices like robots are used to save energy in warehouses. Further robot operations are optimised to improve the efficiency and effectiveness of the robot. Robot trajectory planning is an important problem to be optimised. It reduces the time and energy consumption of the robot in performing an operation. So multi objective optimal trajectory planning will save energy and improve the productivity. In a mixed load palletising operation, the trajectory planning of the robot is very important to do pick and place operation of the objects in an efficient and safer way. Trajectory planning means moving robot end effector in an optimal way from starting point to goal point by considering kinematic, dynamic and geometric constraints. The constraints to be considered are robot joints limits on velocity, jerk, acceleration and torque. Other important constraints are obstacle avoidance, payload constraint, kinematic constraints (positional limits) and geometrical constraints like work volume limits. The trajectory is expressed in time sequence of robot joints displacement, acceleration, velocity and jerk values. Planning trajectory can be done in two coordinate systems. They are Cartesian coordinate system and joint space coordinate system. The later system has some advantages. For example, control system can be directly controlled by the programmer. If the trajectory is in world coordinate system (Cartesian coordinate system), once again it has to be converted by the software to local coordinate system values.

The planned trajectory needs to satisfy some criteria like minimum travelling time, actuators energy consumption, robot joints accelerations, robot joints jerks and actuator torques. While robot end effector is travelling through the planned trajectory, there should not be any collision with obstacles. There should not be any singular points for the robot joints. This can be achieved by considering manipulability index. To increase the productivity, travelling time, speed and actuator effort of robot end effector needs to be an optimum value. To reduce the vibrations and to get smooth movement for robot end effector, robot joints accelerations and jerks are to be optimised. Robot geometric, kinematic, dynamic and payload constraints have to be considered. A suitable curve representation to define a trajectory is to be used. A suitable optimisation technique has to be used to solve the trajectory planning problem. Researchers have used many techniques.

Chiddarwar and Ramesh Babu (2012) considered minimum travelling time, actuators energy consumption, robot joints accelerations, robot joints jerks, collision with obstacles, singular points for the robot joints, geometric, kinematic, dynamic and payload

constraints. They used cubic trigonometric spline. Further they used artificial neural network and VEPSO algorithm.

Cong et al. (2010) considered minimum travelling time and robot joints jerks. They used cubic spline and fuzzy genetic algorithm.

Many researchers considered different objective functions for robot trajectory planning. Huang et al. (2018) considered minimum travelling time and robot joints jerks as objective functions. Xidias (2018) considered minimum travelling time as an objective function. Zhu et al. (2015) considered minimum travelling time as an objective function. Abe and Komuro (2015) considered actuators energy consumption as main criteria. Zhu et al. (2015) considered actuators energy consumption and robot joints accelerations as the goals.

Different curve representations were used to define the trajectory. Guo et al. (2016) used quadrinomial and quintic polynomials. Yu et al. (2009) used cubic b-spline. Zhu et al. (2015) used quintic polynomial spline.

Many optimisation techniques were used by the researcher to solve real world problems. Guo et al. (2016) used ant lion optimiser (ALO) algorithm. Jiang et al. (2015) used DE algorithm. Rai et al. (2011) used BRG LifeMOD simulation software. Tang et al. (2016), To et al. (2009) and Zhu et al. (2015) used genetic algorithm. To et al. (2009) used customised gradient based method.

From the literature review, the following points have been arrived:

- 1 there is no literature dealt the multi objective optimal robot trajectory planning for mixed load palletising operation in a warehouse
- 2 for robot trajectory planning in a palletising operation, the important objective functions are robot end effector travelling time and actuators efforts
- 3 geometric limitations, kinematic bounds and dynamic constraints of the robot have to be considered
- 4 obstacle avoidance criterion has to be considered for getting a feasible trajectory for the robot
- 5 there is no literature dealt the productivity improvement for a warehouse robot which does mixed load palletising operation.

This is the main limitation of the existing work. To overcome the above limitations, this paper presents a multi objective optimal robot trajectory planning method for productivity improvement of a warehouse robot which does mixed load palletising operation.

The paper presents a new strategy for the optimal time-energy trajectory planning of an industrial robot manipulator (MTAB ARISTO 6XT). A new obstacle avoidance method is proposed. The advantages of our method over other methods are:

- 1 it considers all necessary considerations multi objective optimal robot trajectory planning
- 2 it presents a new strategy and a new obstacle avoidance method for the optimal time-energy trajectory planning of an industrial robot manipulator (MTAB ARISTO 6XT).

The trajectory is represented by a cubic NURBS curve. To get a practical trajectory, limits on joints position, acceleration, velocity, jerk and torque are considered. The control points of NURBS functions which defines the trajectory is considered as variables. The MTAB ARISTO 6XT robot model is derived from the Denavit-Hartenberg parameters. Mechanical energy of robot actuator's action is found from Euler-Lagrange's equations by Lagrange's energy function. Two nature based algorithms such as multi objective particle swarm optimisation (MOPSO) and multi objective differential evolution (MODE) are used to find optimal time-energy trajectory.

The rest of the paper is grouped as follows: Section 2 has the problem description, kinematic and dynamic model, trajectory representation and obstacle avoidance. In Section 3, a numerical example to get the optimal time-energy trajectory planning for an industrial robot (MTAB ARISTO 6XT) is presented. In Section 4, two nature based algorithms such as MOPSO and MODE used to find optimal time-energy trajectory are presented. Section 5 describes the mixed load palletising operation. Section 6 deals the productivity and economic study. Section 7 explains Pareto optimality concept. In Section 8, a comparison between the results obtained from various methods is given. The conclusions are given in Section 9.

2 Problem formulation

The industrial robot manipulator examined in this paper is MTAB ARISTO 6XT (Figure 1) with six degrees of freedom (DoF). The aim is to move robot's end effector from starting point to end point along an optimal trajectory. The optimal trajectory is to be obtained by minimising travelling time and the mechanical energy of robot actuators. Physical constraints and actuator limits such as limits on position, acceleration, velocity, jerk and torque of robot joints have to be considered. So this optimisation problem has two objective functions, 288 variables (control points B_i of NURBS functions that represent the trajectories) and 30 constraints.

Figure 1 MTAB ARISTO 6XT robot (see online version for colours)



The multi objective optimisation problem is below:

$$F_1 = T \quad (1)$$

$$F_2 = \int_0^T \sum_{i=1}^n (u_i(t))^2 dt \quad (2)$$

Subject to

- 1 limit on robot joints displacement

$$\max |q_{ij}(t)| \leq QC_j \quad (3)$$

- 2 limit on robot joint velocity

$$\max |\dot{q}_{ij}(t)| \leq VC_j \quad (4)$$

- 3 limit on robot joints acceleration

$$\max |\ddot{q}_{ij}(t)| \leq WC_j \quad (5)$$

- 4 limit on robot joints jerk

$$\max |J_{ji}(t)| \leq JC_j \quad (6)$$

- 5 torque constraint

$$|u_i(t)| \leq u_{ji}^{\max} \text{ for } j = 1, 2, \dots, n \text{ and } i = 1, 2, \dots, m-1 \quad (7)$$

- 6 obstacle avoidance constraint.

Here, The travelling time of end effector is given as F_1 , F_2 is quadratic average of actuator torques, total travelling time between initial and final configurations of robot end effector is T , the generalised forces are given by u_i .

$q_{ij}(t)$ is robot joint displacements, QC_j is maximum robot joint displacements, \dot{q}_{ij} is robot joint velocities, VC_j is maximum robot joint velocities, \ddot{q}_{ij} is robot joint accelerations, WC_j is maximum robot joint accelerations, $\ddot{\ddot{q}}_{ij}$ is robot joint jerks, JC_j is maximum robot joint jerks, $u_i(t)$ is robot joint actuator torques, u_{ji}^{\max} is maximum robot joint actuator torques.

2.1 Description of robot kinematic and dynamic models

The generalised forces are calculated as follow (Saravanan et al., 2010):

$$u_i = \sum_{j=1}^n D_{ij} \ddot{q}_j + I a_i \ddot{q}_i + \sum_{j=1}^n \sum_{k=1}^j C_{ijk} \dot{q}_j \dot{q}_k + G_i + F_{diss,i} \quad i = 1, \dots, n \quad (8)$$

$$D_{ij} = \sum_{p=\max(i,j)}^n \text{Tr} \left[U_{pj} J_p (U_{pi})^T \right] \quad (9)$$

$$C_{ijk} = \sum_{p=\max(i,j,k)}^n \text{Tr} \left[U_{pjk} J_p (U_{pi})^T \right] \quad (10)$$

$$G_i = \sum_{p=1}^n -m_p g^T (U_{pi} \overline{r_p}) \quad (11)$$

Here, the inertial system matrix is denoted by D_{ij} , coriolis and centripetal forces matrix is denoted by C_{ijk} and the gravity-loading vector is mentioned by G_i .

The energy dissipation with consideration of both the friction (coulomb) and the linear viscous damping is given by

$$F_{diss} = f_c \text{sign}(\dot{q}) + f_d \dot{q} \quad (12)$$

$$\text{Coulumb force coefficients} = f_c (\text{Nm}) = [0.058, 0.058, 0.058, 0.056, 0.056, 0.056]$$

$$f_d (\text{Nm/s}) = [0.0005, 0.0005, 0.000472, 0.000382, 0.000382, 0.000382]$$

= Viscous damping coefficients

2.2 Trajectory representation

In the problem, the starting point, ending point and intermediate points to construct the robot joints trajectories are given. In this work, a cubic NURBS curve defines robot's joints trajectory. The main advantages of NURBS curves are smoothness and the possibility of local modifications. So, NURBS curve functions define robot trajectories. Sample applications of NURBS curves are in software tools for animation, computer graphics, surface modelling and part modelling using computer-aided design and manufacturing.

NURBS function is described by equation (13):

$$P(u) = \frac{\sum_{i=0}^n N_{i,k}(u) w_i B_i}{\sum_{i=0}^n N_{i,k}(u) w_i} \quad (13)$$

This equation gives the displacement details of robot joints.

Velocity of robot joints $P'(u)$ are calculated by equation (14):

$$P'(u) = \frac{\sum_{i=0}^n N_{i,k}(u) w_i \sum_{i=0}^n N'_{i,k}(u) w_i B_i - \sum_{i=0}^n N'_{i,k}(u) w_i \sum_{i=0}^n N_{i,k}(u) w_i B_i}{\left(\sum_{i=0}^n N_{i,k}(u) w_i \right)^2} \quad (14)$$

Acceleration of robot joints $P''(u)$ are calculated by equation (15)

$$P''(u) = \frac{\sum_{i=0}^n N_{i,k}(u) w_i \sum_{i=0}^n N''_{i,k}(u) w_i B_i - \sum_{i=0}^n N''_{i,k}(u) w_i \sum_{i=0}^n N_{i,k}(u) w_i B_i}{\left(\sum_{i=0}^n N_{i,k}(u) w_i \right)^2} - \frac{2 \sum_{i=0}^n N'_{i,k}(u) w_i \left(\sum_{i=0}^n N_{i,k}(u) w_i \sum_{i=0}^n N'_{i,k}(u) w_i B_i - \sum_{i=0}^n N_{i,k}(u) w_i B_i \sum_{i=0}^n N'_{i,k}(u) w_i \right)}{\left(\sum_{i=0}^n N_{i,k}(u) w_i \right)^3} \quad (15)$$

Jerk of robot joints $P'''(u)$ are calculated by equation (16):

$$\begin{aligned}
 P'''(u) = & \frac{1}{\left(\sum_{i=0}^n N_{i,k}(u) w_i \right)^2} \left(\sum_{i=0}^n N'_{i,k}(u) w_i \sum_{i=0}^n N'_{i,k}(u) w_i B_i \right. \\
 & + \sum_{i=0}^n N_{i,k}(u) w_i \sum_{i=0}^n N''_{i,k}(u) w_i B_i - \sum_{i=0}^n N''_{i,k}(u) w_i \sum_{i=0}^n N'_{i,k}(u) w_i B_i \\
 & \left. - \sum_{i=0}^n N'''_{i,k}(u) w_i \sum_{i=0}^n N_{i,k}(u) w_i B_i \right) \\
 & - \frac{2}{\left(\sum_{i=0}^n N_{i,k}(u) w_i \right)^3} \left(\sum_{i=0}^n N'_{i,k}(u) w_i \sum_{i=0}^n N_{i,k}(u) w_i \sum_{i=0}^n N'_{i,k}(u) w_i B_i \right. \\
 & - \sum_{i=0}^n N_{i,k}(u) w_i B_i \sum_{i=0}^n N''_{i,k}(u) w_i \sum_{i=0}^n N'_{i,k}(u) w_i \\
 & + \sum_{i=0}^n N''_{i,k}(u) w_i \sum_{i=0}^n N_{i,k}(u) w_i \sum_{i=0}^n N'_{i,k}(u) w_i B_i \\
 & - \sum_{i=0}^n N_{i,k}(u) w_i B_i \sum_{i=0}^n N'_{i,k}(u) w_i \sum_{i=0}^n N''_{i,k}(u) w_i \\
 & + \left(\sum_{i=0}^n N'_{i,k}(u) w_i \right)^2 \sum_{i=0}^n N'_{i,k}(u) w_i B_i \\
 & + \sum_{i=0}^n N_{i,k}(u) w_i B_i \sum_{i=0}^n N'_{i,k}(u) w_i \sum_{i=0}^n N''_{i,k}(u) w_i B_i \\
 & - \sum_{i=0}^n N'_{i,k}(u) w_i B_i \sum_{i=0}^n N'_{i,k}(u) w_i - \sum_{i=0}^n N_{i,k}(u) w_i B_i \sum_{i=0}^n N''_{i,k}(u) w_i \left. \right) \\
 & + \frac{6}{\left(\sum_{i=0}^n N_{i,k}(u) w_i \right)^4} \left(\sum_{i=0}^n N'_{i,k}(u) w_i \right)^2 \sum_{i=0}^n N_{i,k}(u) w_i \sum_{i=0}^n N'_{i,k}(u) w_i B_i \\
 & - \left(\sum_{i=0}^n N'_{i,k}(u) w_i^3 \sum_{i=0}^n N_{i,k}(u) w_i B_i \right)
 \end{aligned} \tag{16}$$

The following recursive formula defines blending function $N_{i,k}(u)$:

$$N_{i,1}(u) = \begin{cases} 1, & u \in [u_i, u_{i+1}] \\ 0, & u \notin [u_i, u_{i+1}] \end{cases} \tag{17}$$

$$N_{i,1}(u) = \begin{cases} 1, & u \in [u_i, u_{i+1}] \\ 0, & u \notin [u_i, u_{i+1}] \end{cases} \quad (18)$$

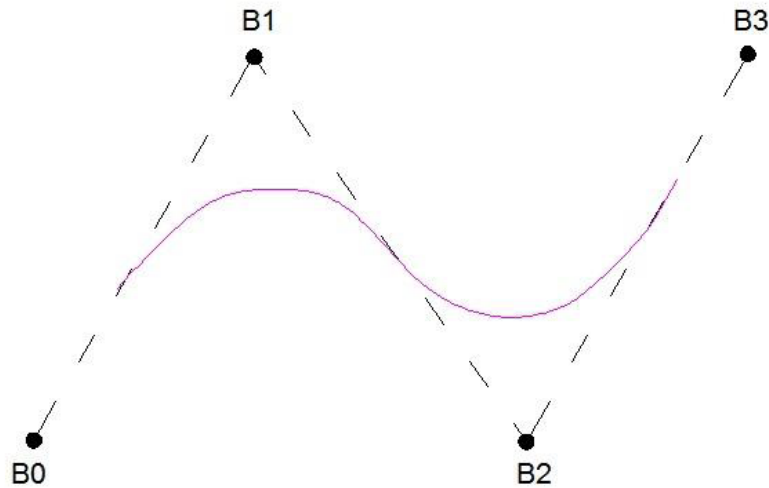
$$N'_{i,k}(u) = k \left(\frac{N_{i,k-1}(u)}{u_{i+k} - u_i} - \frac{N_{i+1,k-1}(u)}{u_{i+k+1} - u_i} \right)$$

$$N''_{i,k}(u) = k(k-1) \left(\left(\frac{N_{i,k-2}(u)}{(u_{i+k} - u_i)(u_{i+k-1} - u_i)} - \frac{N_{i+1,k-2}(u)}{(u_{i+k} - u_i)(u_{i+k} - u_{i+1})} \right) \right. \\ \left. - \left(\frac{N_{i+1,k-2}(u)}{(u_{i+k+1} - u_{i+1})(u_{i+k} - u_{i+1})} - \frac{N_{i+2,k-2}(u)}{(u_{i+k+1} - u_{i+1})(u_{i+k+1} - u_{i+2})} \right) \right) \quad (19)$$

$$N'''_{i,k}(u) = k(k-1)(k-2) \left(\frac{1}{(u_{i+k} - u_i)(u_{i+k-1} - u_i)} \left(\frac{N_{i,k-3}(u)}{(u_{i+k-2} - u_i)} - \frac{N_{i+1,k-3}(u)}{(u_{i+k-1} - u_{i+1})} \right) \right. \\ - \frac{1}{(u_{i+k} - u_i)(u_{i+k} - u_{i+1})} \left(\frac{N_{i+1,k-3}(u)}{(u_{i+k-1} - u_{i+1})} - \frac{N_{i+2,k-3}(u)}{(u_{i+k} - u_{i+2})} \right) \\ - \frac{1}{(u_{i+k+1} - u_{i+1})(u_{i+k} - u_{i+1})} \left(\frac{N_{i+1,k-3}(u)}{(u_{i+k-1} - u_{i+1})} - \frac{N_{i+2,k-3}(u)}{(u_{i+k} - u_{i+2})} \right) \\ \left. + \frac{1}{(u_{i+k+1} - u_{i+1})(u_{i+k+1} - u_{i+2})} \left(\frac{N_{i+2,k-3}(u)}{(u_{i+k} - u_i)} - \frac{N_{i+3,k-3}(u)}{(u_{i+k+1} - u_{i+3})} \right) \right) \quad (20)$$

The knot vector = $[u_i, \dots, u_i + k]$, here u is a parameter, $P(u)$ is nothing but a vector to the point which is got at some value of u , the control points are defined by B_i , $B_i = \{X_i, Y_i, Z_i\}^T$ (in 3D case), n denotes number of control points and the weight factor is defined by w_i . In this optimisation problem, decision variables are NURBS control points B_i .

Figure 2 Trajectory of robot's end effector (see online version for colours)



Three intermediate points are considered in the trajectory. Totally four segments are considered in between starting point and ending point. A cubic NURBS curve with four control points and three intermediate points as in Figure 2 defines each segment.

2.3 Obstacle avoidance

To calculate the robot distance between from obstacle, as per Figure 3, 14 extreme points of the robot have been considered. A stationary obstacle in the shape of rectangular prism is considered in between stacks and pallet. So, eight corner points of rectangular prism have been considered to calculate the robot distance between from obstacle. During motion, the straight line distance between robot extreme points and the obstacle corner points are considered. They should be above the minimum distance to be maintained in order to have the obstacle avoidance. The minimum robot distance from obstacle is to be above 10 cm.

Figure 3 Extreme points of MTAB ARISTO 6XT robot (see online version for colours)



3 Numerical example

In this research work, two nature based algorithms such as MOPSO and MODE are used to find optimal time-energy trajectory for the MTAB ARISTO 6XT robot. The robot can handle 3 kg payload including gripper. Tip speed is 0.2 meter/sec. The gripper can be actuated by pneumatic/electrical drives. Link 1 and link 2 lengths are 300 mm. DC Servo geared motors are used as joint actuators. Vertical height of the robot is 400 mm. For power transmission, Gear train is used in joint 1, ball screw is used in joints 2 and 3, timing belt drive is used in joints 4, 5 and 6. Optical encoder (HP 2 phase 500 PPR) is

used for getting position feedback. 100% gravity compensation is done by non-back drivable ball screw. Number of axes is six (three axes related to waist, shoulder and elbow of manipulator, another three axes related to roll- pitch- roll of spherical wrist).

The velocity and acceleration values are $\dot{q}_1 = \dot{q}_m = \ddot{q}_1 = \ddot{q}_m = 0$ for all joints of robot at starting and end points. The geometrical and inertial arm parameters of MTAB ARISTO 6XT robot are tabulated in Tables 1 and 2. In Table 2, M is mass of a link, I_{xx} , I_{yy} , I_{zz} , I_{xy} , I_{xz} , I_{yz} are moment of inertia of a link about a particular plane, R_x , R_y , R_z is a rotation vector of a link about a particular axis. The kinematic bounds and dynamic constraints are tabulated in Table 3. Robot end effector motion need to be done from initial posture to final posture in consumption of minimum energy and least travelling time. To get a feasible and practical trajectory the minimisation of multi criterion function by considering all robot joints kinematic bounds and dynamic constraints. The payload to be grasped by the MTAB ARISTO 6XT robot is 2.5 kg.

Table 1 MTAB ARISTO 6XT robot – Denavit-Hartenberg parameters

Joint no.	Joint offset (bi)	Joint angle (θi)	Link length (ai)	Twist angle (αi)	Joint angle (θi) min	Joint angle (θi) max
1	322	90	0	90	-150	150
2	0	90	300	0	60	120
3	0	180	0	90	130	190
4	-375	-180	0	90	-210	-150
5	0	0	0	90	-90	90
6	63	0	0	0	-165	165

Table 2 MTAB ARISTO 6XT robot – geometric and inertial parameters

Joint no.	$M(N)$	$I_{xx} (N-m^2)$	$I_{yy} (N-m^2)$	$I_{zz} (N-m^2)$	$I_{xy} (N-m^2)$
0	49.249	0.485	1.117	1.239	-0.011
1	31.277	0.345	0.511	0.520	-0.123
2	15.578	0.043	0.530	0.540	0.004
3	25.298	0.759	0.734	0.203	0.009
4	4.001	0.024	0.009	0.020	0.000
5	1.581	0.004	0.003	0.001	-0.000
6	0.016	0.000	0.000	0.000	0.000
Joint no.	$I_{xz} (N-m^2)$	$I_{yz} (N-m^2)$	$R_x (N-m)$	$R_y (N-m)$	$R_z (N-m)$
0	-0.014	-0.001	-0.068	-0.001	0.110
1	0.019	0.012	-0.105	-0.059	-0.005
2	-0.017	0.000	-0.333	-0.002	0.174
3	-0.024	0.007	-0.032	0.008	0.034
4	0.000	-0.002	-0.000	-0.109	0.008
5	0.000	-0.000	0.000	-0.010	0.033
6	0.000	0.000	-0.000	-0.000	-0.003

Table 3 MTAB ARISTO 6XT robot – limiting parameters

Constraint	<i>Joint number</i>					
	1	2	3	4	5	6
QC(rd)	5.24	1.152	1.047	5.76	5.76	5.76
VC(rd/s)	2	2	2	2	2	2
WC(rd/s ²)	10	10	10	10	10	10
JC(rd/s ³)	50	50	50	50	50	50
UC(N/m)	50	100	75	10	10	10

4 Proposed methods

In this section, two nature based algorithms such as MOPSO and MODE used to find optimal time-energy trajectory for the MTAB ARISTO 6XT robot are described.

4.1 MOPSO algorithm

At present in all fields particle swarm optimisation (PSO) algorithm is used to solve real world problems (Mandal and Mondal, 2017). PSO algorithm advantages are an easy adjustment of parameters, fast convergence, high precision, easy realisation, simple structure, etc. The fitness function need not be differentiable. Because PSO finds the only value of the fitness function. PSO method can be used for optimisation problems of large dimensions. In general, PSO generates quality solutions more quickly than other methods.

Raquel et al. (2005) extended the single objective PSO to solve multi objective optimisation problems. They named it as MOPSO-CD. Crowding distance calculation is included in the algorithm of PSO for selecting global best solution. Non-dominated solutions are stored in an external archive. A mutation operator is introduced with crowding distance computational mechanism to maintain diversity among all non-dominated solutions. The mutation operation is done for all population initially and then it is rapidly reduced over time and generation. The constraint handling mechanism is similar to NSGA-II. An important step in this algorithm is selecting the global best. Because, which affects both diversity and convergence criteria of non-dominated solutions. Any non-dominated solution can be taken as global best solution. But to ensure the search in all directions, the global best guide is selected based on crowding distance calculation. Usually the solution with highest crowding distance is considered as global best guide. So the search is moved to all dimensions. When the external archive for non-dominated solutions is filled, then based on crowding distance calculation the solutions are replaced. The solution in highly crowded region is replaced by the new solution in order to maintain good spread of solutions. So the algorithm results in diversity and good solution spread.

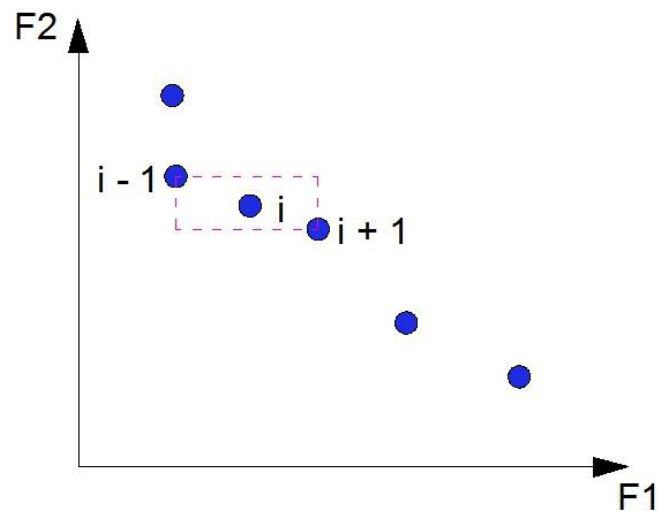
4.2 Multi objective differential evolution

Babu and Anbarasu (2005) presented MODE algorithm to solve multi objective optimisation problems. DE is a variant of GA. So it has operators like mutation,

crossover and reproduction. It is a floating-point encoded algorithm category. MODE is a very simple algorithm and it is computationally inexpensive one. Because it has only less number of function calculation and it needs less memory storage. CPU running time is very low. Its structure is simple and easy to use. But it solves all types of complex problems. At present MODE algorithm is used in almost all fields.

At first a set of solutions NP as per population size are randomly generated. Then solutions are ranked based on dominance concept. DE operators such as mutation and cross over are performed. Noisy vector is prepared by performing mutation operation. Trial vector is created by doing cross over. Then target vector is prepared by reproduction operation. The major difference between DE and MODE is in creation of target vector. In DE, target vector is prepared by comparing trial vector and the parent vector. But in MODE, both trial vector and parent vector are combined. So 2 NP solutions are obtained. Then solutions are ranked according to crowding distance calculation. The best NP solutions are put in the target vector based on solutions ranking and the crowding distance. The solutions with more crowding distance will be given priority. Target vector is assigned as parent vector for next iteration. Thus next generation parent vector is generated.

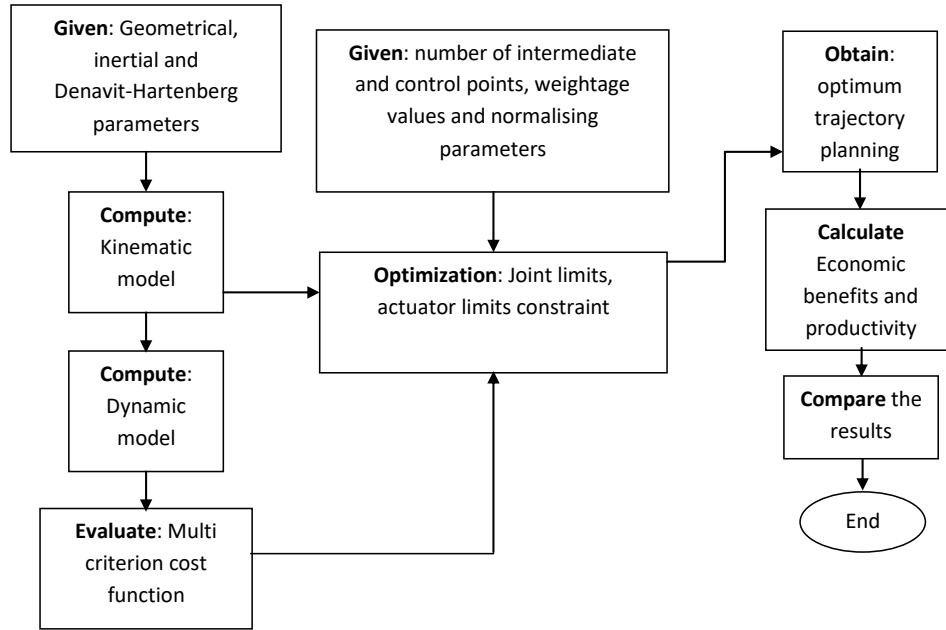
Figure 4 Crowding distance computation (see online version for colours)



As per Figure 4, the crowding distance represents density of solutions in a solution region. First all solutions are arranged in an ascending order based on their fitness values. Crowding distance for a particular solution is found by considering a cuboid. Crowding distance is calculated for a particular solution I by considering its front and back neighbouring solutions. Crowding distance is an average distance between a solution I and its two adjacent solutions. This calculation is done for all solutions. The crowding distance for neighbouring solutions is less. It is very high for the boundary solutions. The boundary solutions have highest and lowest objective function values. In this case, crowding distance may be infinite. So, always boundary solutions will be selected to maintain diversity and to have good solution spread. Summation of crowding distance of all individual objective function values gives final crowding distance for a particular

solution. This procedure is done up to maximum number of generation i.e. up to termination criteria. Figure 5 shows a flowchart of the numerical procedure used in this optimal trajectory planning scheme.

Figure 5 Flowchart of the numerical procedure used in this optimal trajectory planning scheme



4.3 MOPSO operators

4.3.1 MOPSO parameters values are

Population size = 100, variable type = real variable, maximum size of the archive containing the non-dominated points = 250, mutation probability (pMut) = 0.4, acceleration coefficients = $C1 = C2 = 1.0$, inertia weight = $w = 0.4$, total no. of generations = 100.

4.4 MODE operators

4.4.1 MODE parameters values are

Strategy = MODE/rand/1/bin, crossover constant $CR = 0.7$, number of population $NP = 100$, total no. of generations = 100 and $F = 0.5$.

5 Mixed load palletising operation

As per Figure 6, a mixed load palletising operation is considered. Three different parts are to be placed in the ballet. So, three stacks A, B and C are considered. The stack A dimensions are $90 \times 60 \times 30$ cm and it has two layers. So on the top layer; it can

accommodate six parts and another six parts in bottom layer. The stack B dimensions are $40 \times 40 \times 10$ cm and it has one layer. So it can accommodate four parts. The stack C dimensions are $60 \times 60 \times 20$ cm and it has two layers. So on the top layer; it can accommodate nine parts and another nine parts in bottom layer. The pallet dimensions are $120 \times 120 \times 120$ cm and it has one layer. So it can accommodate 16 parts. A stationary obstacle is considered and its dimensions are $10 \times 200 \times 50$ cm. The robot has to transfer 16 parts as per Table 4.

Figure 6 Mixed load palletising operation (see online version for colours)

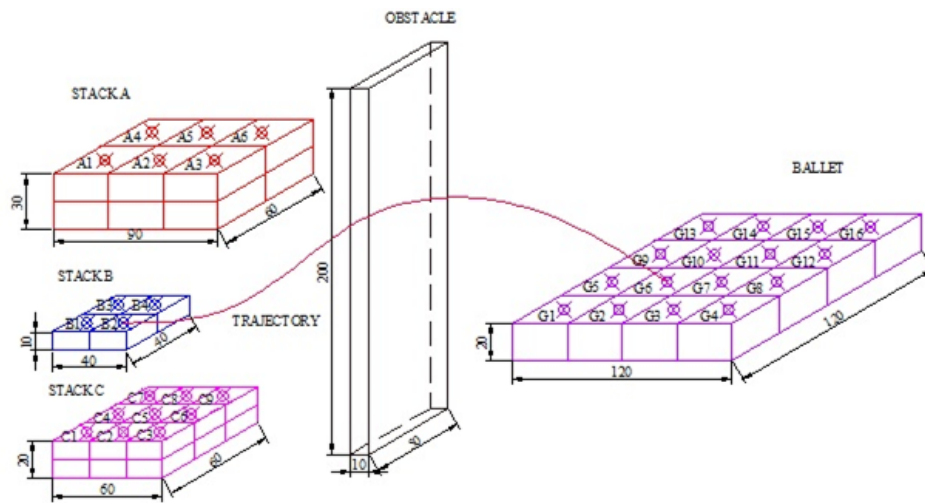


Table 4 Material transfer sequence table

Sl. no	Task no.	Start point	Goal point
01	T1	A1	G1
02	T2	A2	G2
03	T3	A3	G3
04	T4	A4	G4
05	T5	B1	G5
06	T6	B2	G6
07	T7	B3	G7
08	T8	B4	G8
09	T9	C1	G9
10	T10	C2	G10
11	T11	C3	G11
12	T12	C4	G12
13	T13	C5	G13
14	T14	C6	G14
15	T15	C7	G15
16	T16	C8	G16

Table 5 Details of starting and goal points location

<i>Sl. no.</i>	<i>Point</i>	<i>Coordinates (x, y)</i>
01	A1	58.4, 203.4
02	A2	88.4, 203.4
03	A3	118.4, 203.4
04	A4	84.4, 218.5
05	A5	114.4, 218.5
06	A6	144.4, 218.5
07	B1	48.6, 114.6
08	B2	68.6, 114.6
09	B3	65.9, 124.6
10	B4	85.9, 124.6
11	C1	48.6, 55.0
12	C2	68.6, 55.0
13	C3	88.6, 55.0
14	C4	65.9, 64.9
15	C5	85.9, 64.9
16	C6	105.9, 64.9
17	C7	83.0, 74.8
18	C8	103.0, 74.8
19	C9	123.0, 74.8
20	G1	309.8, 121.9
21	G2	339.8, 121.9
22	G3	369.8, 121.9
23	G4	399.8, 121.9
24	G5	336.1, 137.1
25	G6	366.1, 137.1
26	G7	396.1, 137.1
27	G8	426.1, 137.1
28	G9	362.4, 152.3
29	G10	392.4, 152.3
30	G11	422.4, 152.3
31	G12	452.4, 152.3
32	G13	388.7, 167.4
33	G14	418.7, 167.4
34	G15	448.7, 167.4
35	G16	478.7, 167.4

6 Productivity and economic study

The productivity is found from an economic analysis based on robot end effector travelling time. If flexible manufacturing system (FMS) is considered, the goal is to increase production lines profits by changing the production time in assembly lines or by changing the products to be manufactured according to present market demand. Market is ever changing one. By doing changes in production line or assembly line, the company can able to survive in the competitive market.

In this research problem, this is done by generation of an optimal trajectory planning by using some optimisation techniques such as MOPSO and MODE. The optimisation techniques MOPSO and MODE find minimum time and energy trajectory planning for MTAB Aristo 6XT robot by considering geometric, kinematic and dynamic constraints. Then economic study is conducted in this process.

Pareto fronts are found to find which variables are affecting the productivity. Pareto fronts between benefits obtained Vs travelling time of end effector are found for different cases. Pareto front offers some trade off solutions to the user choice. So the user will select any solution according to the present need of the user. Here the productivity is calculated in terms of travelling time of robot end effector. So the objective function of this economic study is given by the below formula:

$$MaxB = \frac{1}{(1+r)^T} \left[\sum_{p=1}^n (P_p - C_p) N_p(t) \right]$$

Here

B	Net benefit from a task accomplished by the robot and it is to be maximised (\$)
Net benefit	Revenue of the products produced in a production line – total costs involved in manufacturing the products.
r	annual discount rate
T	number of years
P_p	Market price for one unit of the product p (\$)
C_p	Production cost for one unit of the product p (\$) including direct and indirect costs like labour wage, raw materials cost, utilities cost, machining cost, material handling cost, maintenance cost, labour training cost, investment costs, operating costs, inventories cost, scrap and rework cost, material saving cost, taxes, etc.
$N_p(t)$	A function related to number of products manufactured per hour and which is found as below:

$$N_p(t) = K / t(S_k)^\mu$$

Here

S_k	Set of activities involved in manufacture and assemble the product p
-------	--

k	Number of activities involved in manufacture and assemble the product p
$t(S_k) = \sum_{j \in S_k} t_j$	Total production time of the product p = sum of time for all activities involved in production of the product A third order function of t_{min} is considered here
μ	a parameter which represents the market seasonality and the economic environment
K	A constant which represents the current no. of working hours/year.

Here the robot's end effector is doing all material handling tasks. These tasks are defined by robot end effector travelling time. The travelling time is depends on the optimal trajectory. Two optimisation algorithms such as DE and PSO find the optimal trajectory. Also they give the minimum time t_{min} required to move the robot's end effector along the optimal trajectory. Manufacturing time depends on material handling time. If the material handling time is reduced, more number of tasks can be performed. So, more number of products/hour can be manufactured.

The total time involved to perform all activities is defined by the following formula:

$$t(S_k) = t_{minp} + \sum_{j \in S_{robot}}^k t_j$$

MRP = marginal revenue of the product = another revenue created by the company by producing additional products by utilising the time saved by the operation of the robot's end effector (t_{min}). The company's total income is increased by this production of additional products.

Further, the additional money added to the total income of a company for a particular period is termed as marginal revenue of product (MRP).

This factor is addressed as additional products manufactured/hour due to reducing the time spent by robot arm (t_{min}). The additional products manufactured will increase company's output and total revenue.

The MRPs is found by multiplying the total number of marginal products (MP) and the product price (PP). To calculate price of a product P_p , market-determined price of a product need to be considered. If the company is having perfect competitive market, then Marginal Revenue is given by $MRP = MP \times P_p$.

If marginal revenue decreases means, it indicates that time saved by the robot decreases. If time saved by the robot increases, the marginal revenue increases and the company gets more profit.

7 Pareto optimality

Majority real world problems are having more than one objective functions. Minimum two to three objective functions and they are also in conflicting nature. For example, if a company needs to earn more profit means it has to cut down the manufacturing cost without compromising the product quality. In general, if the product quality high means, manufacturing cost is high. But the need is the company has to reduce the manufacturing

cost without reducing the product quality. Practically it is not possible to reduce the manufacturing cost beyond certain level without compromising the quality. No improvement can be done in one objective function without affecting another objective function, i.e., only by minimising the quality, the production cost can be reduced.

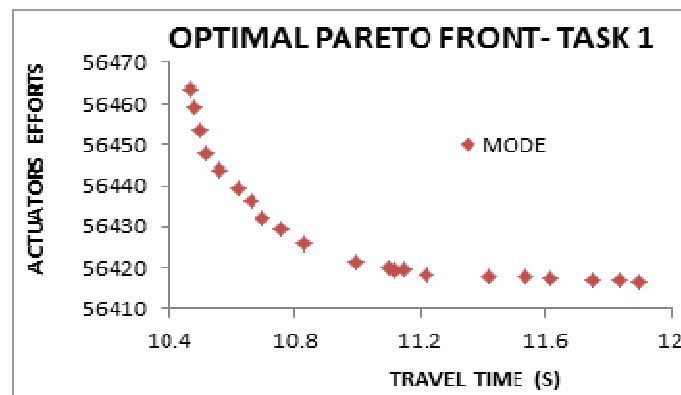
To handle this situation, multi objective optimisation algorithms offer a Pareto front to the user instead of suggesting a single solution. The Pareto front has more number of non dominating solutions. Non dominating solutions mean that one solution cannot be said as superior or inferior to another solution. So by giving preference (weightage to objective functions) only the user can say one solution is better to another solution. The set of equal importance optimal solutions is termed as Pareto-optimal set in Multi objective optimisation field. The Pareto front could be concave or convex and continuous or discontinues. User cannot predict it before solving the problem.

In this research problem, the benefits for material handling task is depends on the movement of the robot's end effector. The time taken by the robot's end effector to travel along a trajectory determines the benefits. Travelling time depends on the distance of the travel. So, to minimise the travel time, travel distance is to be minimised. But practically, the distance to be travelled cannot be reduced beyond certain limit. This is due to obstacle avoidance, safe handling of the job, safer movement of the robot, minimisation of vibrations, speed of the robot's end effector needs to be less than its safer speed, singularity avoidance and constraints on acceleration, velocity, jerk and actuator torque of robot joints. So multi objective optimisation problems such as MOPSO and MODE give Pareto-optimal fronts for the selection convenience of the user. By giving suitable weightage, the user will select a best

8 Results and discussions

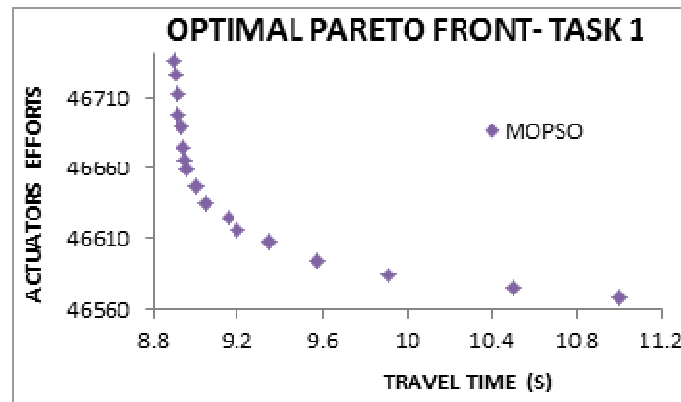
The considered multi load palletising operation has 16 moves (tasks) from stacks to pallet. The considered industrial robot does all tasks. In two stages, the performance of the robot is improved. First stage is for finding optimal trajectory planning by considering both travel time and energy as objective functions. Second stage is for economic analysis and productivity improvement of robot tasks, i.e., both travel time and economic benefits are taken as objective functions.

Figure 7 Pareto optimal front from MODE for task 1 (stage 1) (see online version for colours)



In first stage, multi objective optimal trajectory planning is done. Minimisation of both time and energy (actuator efforts) requirements of robot end effector travel are done in a multi objective approach. All constraints related to geometric, kinematic and dynamic constrains are considered. Also obstacle avoidance is included in generating each and every optimal solution in all generations. DELL OptiPlex 3,040 computer system (with configuration of 2 GB DDR3L RAM, 1 TB HDD, Pentium dual core Processor, Microsoft windows 8 OS) is used for running the algorithms. Figures 7 and 8 show Pareto optimal front got from MODE and MOPSO algorithms for Task 1 in stage 1.

Figure 8 Pareto optimal front from MOPSO for task 1 (stage 1) (see online version for colours)



In second stage the economic objective function is considered for improving productivity of mixed load palletising operation. The economic benefits, costs and price are calculated for the optimal solutions in Pareto-fronts of MOPSO and MODE algorithms. The following values are assigned for economic analysis: Number of product produced is one.

r annual discount rate = 0.05

T number of years = 1 year

P_p Market price for one unit of the product (p) (\$) = \$1.0

C_p Production cost for one unit of the product (p) (\$) including direct and indirect costs like labour wage, raw materials cost, utilities cost, machining cost, material handling cost, maintenance cost, labour training cost, Investment costs, operating costs, inventories cost, scrap and rework cost, material saving cost, taxes, etc. = \$0.8

k Number of activities involved in manufacture and assemble the product (p) = 16

Total production time of the product (p) = 90 seconds (excluding robot end effector travelling time)

μ a parameter which represents the market seasonality and the economic environment = 0.6.

K A constant which represents the current no. of working hours/year = 365×8 (1 shift operation of 8 hours has been considered. 365 days are considered for a year)

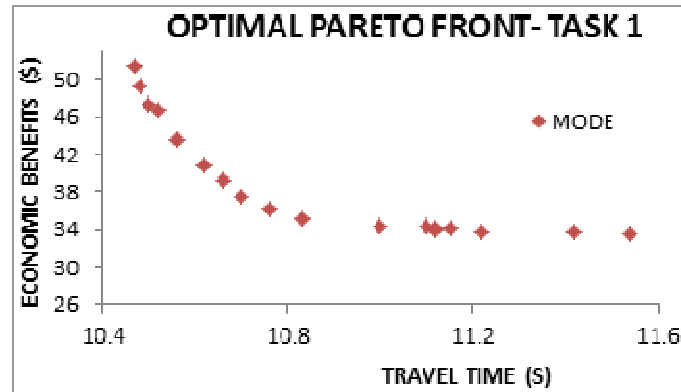
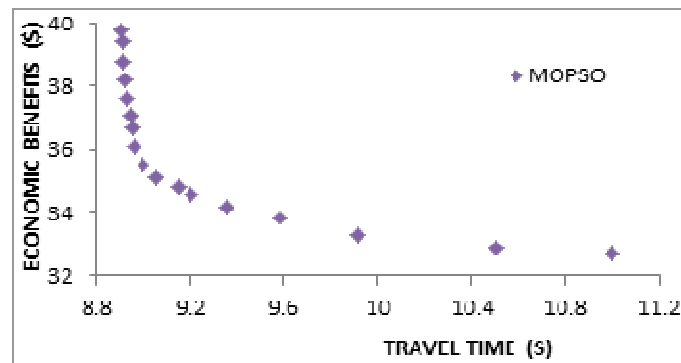
From Table 6, it is observed that MOPSO gives better results in terms of travel time, actuators effort and economic benefits than those of MODE.

Table 6 MOPSO and MODE results

Task number	MOPSO results for equal weightage to both objective functions F_1 and F_2			MODE results for equal weightage to both objective functions F_1 and F_2		
	Optimum travel time ($F_1 = T$) (Sec.)	Optimum actuators efforts (F_2)	Economic benefits (\$)	Optimum travel time ($F_1 = T$) (Sec.)	Optimum actuators efforts (F_2)	Economic benefits (\$)
T1	9	46,647.5	35.5	11	56,421.7	34.3
T2	9	46,547.4	35.8	10	51,247.8	33.2
T3	8	40,643.8	35.8	10	51,223.4	32.1
T4	8	40,112.2	36.2	9	46,572.8	34.5
T5	6	31,245.5	32.4	8	41,354.2	30.4
T6	6	31,462.4	32.6	8	41,225.4	30.4
T7	6	31,142.9	32.1	7	36,642.2	31.1
T8	5	26,342.1	31.9	7	36,541.2	29.5
T9	7	37,234.4	33.8	9	46,251.2	31.6
T10	6	31,574.2	33.5	8	41,243.3	30.5
T11	6	31,245.3	33.4	8	41,142.5	30.2
T12	5	26,472.5	33.75	8	41,010.1	30.2
T13	7	37,578.5	33.6	9	46,321.7	31.8
T14	6	31,452.7	33.42	8	41,247.5	30.5
T15	5	26,324.5	33.7	8	411,654.9	30.1
T16	5	26,212.2	33.51	7	364,72.5	30.1

Figures 9 and 10 show Pareto optimal front got from MODE and MOPSO algorithms for Task 1 in stage 2. From the Figures 7–10 and Table 6, the following points have been observed:

- 1 For all optimal solutions in the pareto fronts gave by both MOPSO and MODE, the robot joints displacements, accelerations, velocities, jerks and actuator torques are well within the limits. Also they satisfy the obstacle avoidance criterion. So the resulted trajectories are feasible and practically possible.
- 2 Regarding convergence, MOPSO converges quickly within fewer generations compared to MODE. Also MOPSO algorithm running time is less than that of MODE algorithm. So MOPSO is faster than MODE.
- 3 But MODE algorithm gives more number of optimal solutions in pareto-optimal front than that of MOPSO.
- 4 MOPSO gives better results in terms of travel time, actuators effort and economic benefits than those of MODE.

Figure 9 Pareto optimal front from MODE for task 1 (stage 2) (see online version for colours)**Figure 10** Pareto optimal front from MOPSO for task 1 (stage 2) (see online version for colours)

9 Conclusions

This research work describes a multi objective robot optimal trajectory planning for mixed load palletising operation. Multi objective robot optimal trajectory planning is carried out in two steps. In the first step, both travel time and actuators effort are taken as objective functions. In the second stage, the travel time and economic benefits are taken as objective functions. All practical considerations like limits on robot geometric, kinematic and dynamic parameters are considered. Two algorithms MOPSO and MODE are used. From this research work, the following conclusions are derived:

- 1 Both MOPSO and MODE gave good Pareto fronts which have more number of optimal solutions for users' choice.
- 2 The resultant trajectories are practically possible and feasible.
- 3 MOPSO is faster than MODE.
- 4 MOPSO gives better results in terms of travel time, actuators effort and economic benefits than those of MODE.

- 5 But MODE algorithm gives more number of optimal solutions in pareto-optimal front than that of MOPSO.
- 6 Mixed load palletising operation is a build-to-order operation. So it ensures rapid delivery of goods to customers.
- 7 The proposed method reduces the time between order placing and the order supplying.
- 8 The green supply chain can reduce the cost and time to deliver the ordered items to customers.
- 9 The proposed method can help the Eco friendly warehouse which has the ability to help zero-defect logistics and increase in productivity.
- 10 The proposed method helps the Eco friendly warehouse to get relief from the hurdles in order packaging.
- 11 This multi objective optimisation on Eco friendly warehouse robot trajectory planning increases the green supply chain profits.

So the green logistics industries can do some wonders in Eco friendly warehouse, meet demands of consumers and withstand in ever changing markets.

Future work of this research is to build some mobile robots to replace order delivery labours. So the green supply chain can get more benefits. Another future work is integrating more innovative technologies like intelligent sensors, Voice control headsets, Smart watches and smart glasses, Internet of Things, etc in Eco friendly warehouse operations.

References

- Abe, A. and Komuro, K. (2012) 'Minimum energy trajectory planning for vibration control of a flexible manipulator using a multi-objective optimisation approach', *International Journal of Mechatronics and Automation*, Vol. 2, No. 4, pp.286–294.
- Alvarez-de-los-Mozos, E. and Renteria, A. (2017) 'Collaborative robots in e-waste management', *Procedia Manufacturing*, Vol. 11, pp.55–62.
- Babu, B.V. and Anbarasu, B. (2005) *Multi-Objective Differential Evolution (MODE): An Evolutionary Algorithm for Multi-Objective Optimization Problems (MOOPs)* [online] https://www.researchgate.net/publication/228924019_Multi-objective_differential_evolution_MODE_an_evolutionary_algorithm_for_multi-objective_optimization_problems_MOOPs (accessed 11 June 2018).
- Barreto, L., Amaral, A. and Pereira, T. (2017) 'Industry 4.0 implications in logistics: an overview', *Procedia Manufacturing*, Vol. 13, pp.1245–1252.
- Bechtsis, D., Tsolakis, N., Vlachos, D. and Iakovou, E. (2017) 'Sustainable supply chain management in the digitalisation era: the impact of automated guided vehicles', *Journal of Cleaner Production*, Vol. 142, Part 4, pp.3970–3984.
- Chand, M., Raj, T. and Shankar, R. (2015) 'Risk mitigations strategy in supply chain planning and control: an ANP approach', *International Journal of Productivity and Quality Management*, Vol. 16, No.1, pp. 92–113.
- Chiddarwar, S.S. and Ramesh Babu, N. (2012) 'Optimal trajectory planning for industrial robot along a specified path with payload constraint using trigonometric splines', *International Journal of Automation and Control*, Vol. 6, No. 1, pp.39–65.

- Cong, M., Xu, X. and Xu, P. (2010) 'Time-jerk synthetic optimal trajectory planning of robot based on fuzzy genetic algorithm', *International Journal of Intelligent Systems Technologies and Applications*, Vol. 8, Nos. 1–4, pp.185–199.
- Guo, J., Yan, D., Cao, H. and Jiang, H. (2016) 'The point to point trajectory planning based on the ant lion optimizer', *International Journal of Automation and Control*, Vol. 10, No. 2, pp.155–166.
- Huang, L., Hu, P., Wu, K. and Zeng, M. (2018) 'Optimal time-jerk trajectory planning for industrial robots', *Mechanism and Machine Theory*, Vol. 121, pp.530–544.
- Jiang, D., Li, L., Gong, J. and Fan, Z. (2015) 'Optimal trajectory searching based differential evolution', *International Journal of Wireless and Mobile Computing*, Vol. 8, No. 4, pp.384–393.
- Karabegović, I., Karabegović, E.A., Mahmić, M. and Husak, E. (2015) 'The application of service robots for logistics in manufacturing processes', *Advances in Production Engineering and Management*, Vol. 10, No. 4, pp.185–194.
- Kong, X.T.R., Zhong, R.Y., Xu., G. and Huang, G.Q. (2017) 'Robot-enabled execution system for perishables auction logistics', *Industrial Management and Data Systems*, Vol. 117, No. 9, pp.1954–1971.
- Mandal, P. and Mondal, S.C. (2017) 'An application of artificial neural network and particle swarm optimisation technique for modelling and optimisation of centreless grinding process', *International Journal of Productivity and Quality Management*, Vol. 20, No. 3, pp.344–362.
- Merlino, M. and Sproge, I. (2017) 'The augmented supply chain', *Procedia Engineering*, Vol. 178, pp.308–318.
- Rai, J.K., Tewari, R.P., Pandey, S. and Chandra, D. (2011) 'Optimised torque trajectory for humanoid robot based on human gait data', *International Journal of Mechatronics and Manufacturing Systems*, Vol. 4, No. 2, pp.171–184.
- Raquel, C.R. and Naval Jr., P.C. (2005) 'An effective use of crowding distance in multiobjective particle swarm optimization', *2005 Genetic and Evolutionary Computation Conference (GECCO'2005)*, ACM Press, New York, USA, June, Vol. 1, pp.257–264.
- Saravanan, R., Ramabalan, S., Sriram, P. and Balamurugan, C. (2010) 'Non-uniform rational B-spline-based minimum cost trajectory planning for autonomous robots', *International Journal of Intelligent Systems Technologies and Applications*, Vol. 9, No. 2, pp.121–149.
- Tang, Z., Zhou, Q., Qi, F. and Wang, J. (2016) 'Optimal transitional trajectory generation for automatic machines', *International Journal of Computational Science and Engineering*, Vol. 12, Nos. 2/3, pp.104–112.
- To, W.K., Paul, G., Kwok, N.M. and Liu, D. (2009) 'An efficient trajectory planning approach for autonomous robots in complex bridge environments', *International Journal of Computer Aided Engineering and Technology*, Vol. 1, No. 2, pp.185–208.
- Xidias, E.K. (2018) 'Time-optimal trajectory planning for hyper-redundant manipulators in 3D workspaces', *Robotics and Computer-Integrated Manufacturing*, Vol. 50, pp.286–298.
- Yu, J., Fang, Q. and Ke, Y. (2009) 'Trajectory planning of multi-robot coordination platform for locating large subassembly', *International Journal of Modelling, Identification and Control*, Vol. 6, No. 4, pp.357–366.
- Yuan, Z. and Gong, Y. (2016) 'Improving the speed delivery for robotic warehouses', *IFAC Papers Online*, Vol. 49, No. 12, pp.1164–1168.
- Zhang, S., Lee, C.K.M., Chan, H.K., Choy, K.L. and Wu, Z. (2015) 'Swarm intelligence applied in green logistics: A literature review', *Engineering Applications of Artificial Intelligence*, Vol. 37, pp.154–169.
- Zhu, Z., Xu, W., Meng, Z. and Sun, Y. (2015) 'Optimal trajectory and placement of a SCARA robot for natural yarns handling in the lattice distortion modification processing', *International Journal of Mechatronics and Manufacturing Systems*, Vol. 8, Nos. 3/4, pp.85–101.