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Comparative Simulation Study for Configuring Turning Point in Multiple Robot Path Planning: Robust Data Envelopment Analysis

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SUMMARY
This paper concerns with comparing simulation studies for a newly developed concept of turning point to be used in multiple robot path planning. Different critical factors and design parameters are collected and statistical analyses are performed. After configuring different simulation scenarios, the efficient one is evaluated using a robust data envelopment analysis (RDEA). Due to uncertain aspects of various simulations scenarios, robust version of data envelopment analysis is proposed. Here, major criteria in robot path planning are deadlock and conflict avoidance, throughput, mean flow time, and effective total distance travelled. To determine the effective experiment for the proposed simulation model, RDEA is used. A comparative study with respect to different experiments having various simulation setting is developed. The results for a real robotic manufacturing cell system show effectiveness of the proposed process. Also, the efficient simulation software is determined by multiaspect analysis.

KEYWORDS: Robot; Turning point; Simulation; Path planning.

1. Introduction

One of the important industrial segments is material transportation system (MTS). It is due to the fact that customers typically demand for shorter delivery time and lower transportation charge. This puts the organizations under continuous pressure to implement various operational approaches and policies to achieve both aims. Therefore, minimizing delivery time should be conducted efficiently. Robot is one of the MTS used in manufacturing shop floor to move materials between stations in an automated manufacturing system. Robot is preferred over other transportation approaches due to the flexibility and mobility attributes it could offer.

Material handling is one of the widest spread application processes utilized in manufacturing today. While many manufacturers use material handling robot systems, several are moving toward material handling workcells that consist of either one or multiple robots, doing several tasks at one station. A material handling workcell is one of the most versatile workcells available on the market today. While welding workcells are usually confined to either spot- or arc-welding applications, material handling workcells can perform a dozen different tasks depending on the end-of-arm tooling available. In an effort to make manufacturing more efficient, manufacturers are turning more to workcells for material handling. These workcells can perform several tasks within one workcell. Within these workcells, material handlers can work with other robots, Computer Numerical Control (CNC) machines, or even human workers. They can be used to transfer parts into different machines that are positioned around it at one station, or they can take parts from an assembly robot within the

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Fig. 1. A robotic manufacturing cell.

material handling workcell and place them on a turntable or other positioner for a human worker to grab and take to the next area. A robotic manufacturing cell is shown in Fig. 1.

According to statistics in 1989,[1] robot system installations with respect to their application types were profiled as following: just in time delivery systems (56%), flexible manufacturing systems/flexible assembly system (FMS/FAS) transfer system (13%), storage load transfer, non-assembly system/robot system (12%), AS/RS interface (8%), progressive assembly (7%), mini-load AS/RS interface (1%), and others (3%). Some other applications of Autonomous Guided Vehicle (AGV) systems in non-manufacturing environments include, but are not limited to, delivering mail, messages, and packages in offices, and delivering meals and laundry in hospitals.

Typical objectives in design of robot systems include (1) evaluation of the feasibility of an robot system, (2) evaluation of the dispatching rules, (3) elimination of traffic problems, (4) maximizing the reliability, (5) maximizing the vehicle utilization, (6) minimizing the inventory level, (6) minimizing the transportation costs, and (7) maximizing the space utilization. Tools used in robot system design can be classified in two main categories: analytical tools and simulation-based tools. Analytical tools are mathematical techniques such as queuing theory, integer programming, heuristic algorithm, and Markov Chains. A number of analytical approaches to the design of robot systems have been proposed in the literature.[2,3] Fazlollahtabar and Saidi-Mehrabad[4] discussed literature related to different methodologies to optimize robot systems for the two significant problems of scheduling and routing at manufacturing, distribution, transshipment, and transportation systems. They categorized the methodologies into mathematical methods (exact and heuristics), simulation studies, metaheuristic techniques, and artificial-intelligent-based approaches.

Numerous researches worldwide have contributed toward the betterment in developing an efficient robot system. Interestingly, Nouri et al.[5] proposed classification schema for scheduling of job system with transportation resources. Moreover, Luo et al.[6] modeled the integrated vehicle scheduling and container storage problem. Small-sized problems were solved optimally by using mixed-integer programming, while large-sized problems were solved by using genetic algorithm. Meanwhile, cloud architecture has been proposed to coordinate multiple robots within a system.[7] Additionally, several methodologies to optimize the scheduling and routing problems for robot have been reviewed.[4] Moreover, extensive review on researches conducted on robot has been made by Vis.[8] The related researches proposed to analyze vehicle requirement for material transportation in the manufacturing industry have been discussed in detail by Vis et al.[9] Subsequently, Arifin and Egbelu[10] proposed a statistical-based method to estimate the fleet size required. Since then, numerous researches have used the proposed method to solve different problems.

Currently, the robot is a transport vehicle widely used in manufacturing factories and plays an important role in the design of material handling system, moving goods to raw materials or finished product to rightful destination that works automatically. Varagul and Ito[11] designed an obstacle simulation algorithm for robots being used in security of internal transportation system in order to prevent a collision with the robots and the obstacles without knowing the exact shape, size, and color.

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Antakly et al.[12] dealt with the conflict avoidance problem of a robot system in a FMS. Regarding the complexity of this kind of problem, it has generated many works to find an optimal strategy for scheduling and routing robots. A new strategy based on a temporal logic, modeled using time Petri nets, was developed. Valmiki et al.[13] presented an estimation of fleet size of automated guided vehicle (robot). Determination of robot fleet size plays a decisive role on the performance of job shop environment. Simulation methods were studied in detail for the estimation of robot fleet size in a FMS. The presented methods were based on either minimization of total travel time or overall cost.

Simulation software that can be used for robot system simulation can be grouped in three categories:[14] (1) general-purpose simulation languages (e.g., SLAM II and SIMAN IV), (2) simulation packages designed for the general simulation of manufacturing systems (e.g., SIMPLE++, AutoMod II, ProModel, and SIMFACTORY II.5), and (3) simulation software specially created for analyzing robot systems by using general programming languages such as C, FORTRAN, BASIC, and LISP.[2]

The reviewed works for the simulation in the literature mostly focus on the design of a robotic-based system and evaluate different implementation scenarios using different performance criteria, especially time-related ones. Also, the configuration of such a system has been studied for utilization and productivity purposes. An in-depth analysis presents that in the design of robotic systems the aim was based on the routing or scheduling objectives, separately.

This paper presents a comparative simulation model to study the efficiency of a turning point concept in different scenarios of multiple robot paths planning in a manufacturing system. The remainder of this paper is organized as follows. In the next section, the concept of turning point in a manufacturing cell is stated and modeled. The simulation model is designed and described in Section 3. The experiment and analysis in ARENA simulation environment are given in Section 4. The comparative study using robust data envelopment analysis (RDEA) is detailed in Section 5. The final section contains discussions and conclusions.

2. Robotic Manufacturing Cell and Concept of Turning Point

In a modern production facility, automation is a central key to creating competitive advantage and responding to the constantly increasing demands on production. We supply future-oriented and highly automated manufacturing cells based on standardized and flexible cell concepts. Robots are ideal for automated cells—spindles are consistently fed, so machine utilization is high, while grouping equipment close together means secondary operations can also be automated and in-process inventory eliminated. Waste is reduced through early detection of quality problems and less floorspace is needed. Robotic cellular manufacturing is a flexible approach that enables cost-effective automated production of low- and medium-volume product families.

Automated cells can take many forms, with one or more robots performing the handling duties that make everything work together smoothly. Sheet metal bending, stamping, part machining, material removal, and polishing are just some of the processes that can be arranged as cells, automated with a robot. For example, in a machining business, a robot equipped with a double-gripper end-effector could lift a casting from an input conveyor, unload the previous part from a lathe, and chuck the next. While the lathe turns the new casting, the robot might take the machined part to a drill, and then to a wash station. Some automated cells even include inspection before placing the part in a bin or on an outfeed conveyor. Machine utilization is maximized because the robot repeats each cycle with complete consistency and without taking breaks.

Robotic cellular manufacturing cuts costs, improves quality, and increases capacity, but none of that happens without careful planning. The keys to success are first recognizing the challenges and then developing a plan that meets project goals. Material handling robots cut costs because they do the kind of arduous work humans are not suited for. They will lift massive payloads—the largest Fanuc robot can tote more than 2866 pounds (1300 kg) at one time—and place them to within a few thousandths of an inch all day and all night. They thrive in hot, noisy, and dangerous places such as foundries, forges, and strip mills, never taking a break, vacation, or sick leave.

Consider a cell manufacturing system with multiple robots performing material handling. Finding a free path to fulfill the material handling function for robots is important. The overall problem is to determine the manufacturing schedule and routing for robots to minimize the total number of deadlock and conflicts leading to cycle time violation and lost sale. The manufacturing cell elements are listed in Table I and the general layout is shown in Fig. 2.

Table I. Manufacturing cell elements.

No.	Element
1	Input component storage
2	Component and fixture assembly station
3	Handling robot
4	Grinding machine
5	Rotating table
6	Handling/deburring robot
7	Inspection post
8	Deburring device
9	Tooling storage
10	Coordinate measuring machine
11	Output component storage

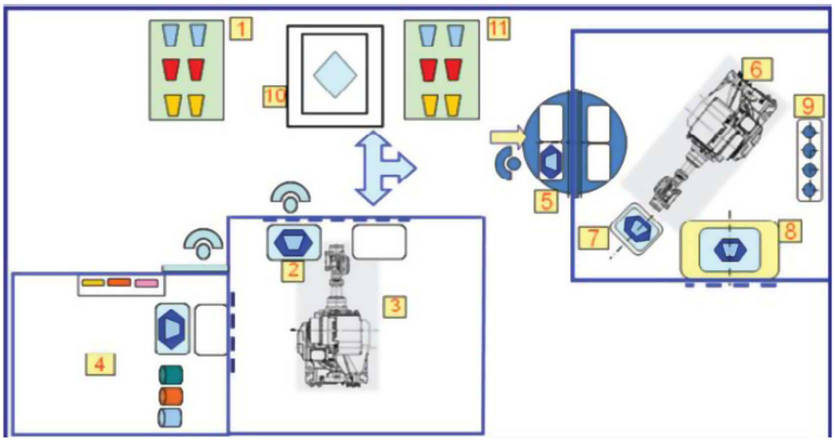

Fig. 2. A general manufacturing cell without “turning point.”

In this research, a new concept of deadlock resolution and conflict-free routing and scheduling is developed. “Turning points” are mounted as guide path distribution centers to prohibit robots’ conflicts during movements. The intersection of guide paths is determined as the turning point. In these points, a robot is directed according to the process plan sent from the control unit and concerning work cells’ demands. The advantage of the turning points is having robots operate nonstop according to the process plan without conflicts with others reducing the amortization costs. This is a deadlock resolution remedy for the manufacturing system. A configuration of the proposed “turning point” in a cell manufacturing is presented in Fig. 3.

3. Simulation Model Configuration

Transport jobs are from different cells to others. For each robot, a destination is drawn from a uniform distribution. Robots travel with constant speed. Except for the destination choice, no stochastic behavior is modeled. Begin and end of the trajectories are discarded; obstacles are avoided using the proposed turning point model.

All robots’ transportation times in the simulation are set to zero. Thus, only driving robots are considered. For the “without turning point” strategy, only the average driven distance is used to compute a possible job performance without taking into account the effects of congestion. Hence, a linear relation between the number of robots and transport capacity is assumed. For the “with turning point” strategy, the turning point is used to reduce the number of deadlocks to zero. Thus, congestion results in non-linear behavior when a large number of robots are employed.

In Table II, the results of the “without turning point” strategy, in Monte Carlo simulation as a verification test, are presented. The number of robots differs between 1 and 40. The resulting number of executed handling tasks is almost linear with the number of robots below 20. In the case more than 20 robots are employed, the number of executed tasks decreases regarding congestion effects.

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Table II. Monte Carlo simulation results of the "without turning point" strategy.

Robots	1	5	10	15	20	25	30	35	40
Jobs/h	57	269	548	823	1054	1296	1385	1625	1748
Deadlocks	0	0	0	0	0	0	0	0	0
Path-conflicts	0	14	138	309	563	908	1298	1812	1321

Table III. Monte Carlo simulation results of the "with turning point" strategy.

Robots	1	5	10	15	20	25	30	35	40
Jobs/h	57	315	508	672	777	812	883	925	963
Deadlocks	0	0	0	0	0	0	0	0	0
Path-conflicts	0	29	159	307	506	781	1153	1324	1659

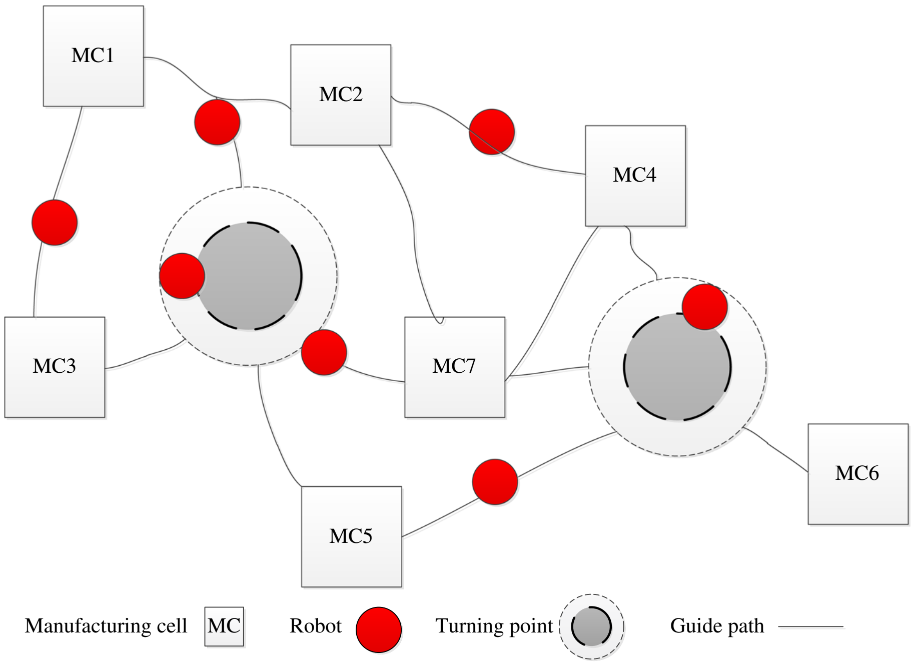

Fig. 3. A configuration of the proposed "turning point" in cell manufacturing.

In Table III, the results of the "with turning point" strategy (having turning point) are shown. It is obvious that the large safety margins cause a faster and larger drop in transport capacity.

In both tables, the number of deadlocks is given; it is shown that both "without turning point" variants are safe, as expected. The so-called "path-conflicts" are the number of occasions that more than one robot occupies the same path. Whether this is a problem or not depends of course on the layout of the system.

4. Discrete Event Simulation for Multiple Robot Cell Manufacturing

Discrete event simulation (DES) refers to simulation that employs mathematical and logical models of a physical system to represent state changes at precise points in simulated time. Taking advantages of the computing advancement, DES has been intensively developed for modeling, simulating, and analyzing dynamic and complex systems. This is meant to enable research on advanced industrial system to be conducted. Among simulation-based researches for manufacturing applications we can imply those conducted by Gupta et al.[15] and Manup and Raja.[16] Consequently, Arena and Simul8 simulation software are used to model material handling operation within a manufacturing cell. There are several advantages of Simul8 software particularly in its ability to accommodate mathematical and logical procedure with relative ease through Visual Logic. Furthermore, it is also possible to integrate codes developed using Visual Basic into the Simul8 simulation framework.

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Table IV. System configuration.

Job no.	Volume mix (%)	Machine sequence (processing time in minutes)
1	25	P 1 (4) – P 2 (8) – P 3 (3) – P 14 (4) – P 17 (1) – P 19 (12) – P 20 (1)
2	25	P 1 (4) – P 2 (8) – P 3 (3) – P 6 (3) – P 7 (1) – P 14 (4) – P 17 (1) – P 19 (12) – P 20 (1)
3	20	P 5 (2) – P 6 (3) – P 7 (1) – P 15 (5) – P 17 (1) – P 19 (15) – P 20 (1)
4	15	P 1 (4) – P 2 (8) – P 3 (3) – P 4 (4) – P 13 (3) – P 14 (4) – P 17 (1) – P 19 (15) – P 20 (1)
5	15	P 8 (3) – P 9 (5) – P 10 (1) – P 11 (8) – P 12 (4) – P 16 (6) – P 17 (1) – P 19 (22) – P 20 (1)

The key points of this step include the critical factors of the system, design parameters (DPs) affecting the system, and the categorization of these factors. Through careful consideration of the above key points, we can design a simulation model and determine the critical factors and DPs that are needed for the experimental design of the model. Then, we must consider the selection of the simulation language or software and the random-number seeds for each design point, the choice of the length of simulation time to reach a steady state, and the verification and validation of the simulation model.[17]

Step (1): Identification of critical factors

In simulation-based design, many critical factors arise. The mutual impact of critical factors might be difficult to predict. It might be hard to decide on one factor or parameter without considering other factors and parameters.[17]

Typical critical factors in the design of the multiple robot system include: (1) minimizing the congestion; (2) maximizing the vehicle utilization; (3) maximizing the reliability; (4) elimination of traffic problems; (5) minimizing the transportation costs; and (6) maximizing the space utilization.

Step (2): Selection of the DP

The DPs for the robot system are involved in the simulation-based design with regard to multi-factorial analysis and the optimization of critical factors. The design of experiments encompasses DPs and operational parameters.[17]

DPs consist of fixed and changed parameters. To separate the fixed and changed parameters, we propose sensitivity analysis. The most general and simple method for analyzing the influence of DPs is the one parameter-at-a-time analysis using a simulation model.

Simulation-based techniques include general-purpose simulation languages, simulation packages for specific systems, and simulation software that is created by using general programming languages.[14,18,19]

In this paper, we consider a comparative study to analyze the effect of turning point in traffic management of a multiple robot cell manufacturing system in two simulation modeling environments.

4.1. Simulation modeling

In this section, the proposed model is implemented using real production data in a simulation environment.

The simulation model is based on tire manufacturing factory. Part of the entire shop floor with process-based layout has been modeled with the intention of studying the vehicle-based material transportation process. The model possesses certain technical specifications and assumptions as the following:

- System specification
  Plant layout used in the manufacturing system is based on cell layout. There are 19 production cells in the system, where each cell has a set of machines. There are five job sets with each possessing specific number of operation sequences. The details of the job sets are described in Table IV. In order to acquire stable data on the production flow, the warm-up period is fixed for 2 h. Thus, data for analysis purpose are only collected after the warm-up period. Job arrival rates of 80 jobs/h with mean, *E*, follow a Poisson distribution.

- Machine specification
  The number of machines, m, in the system is fixed. Machine's processing times are normally distributed with a standard deviation, $\sigma = 0.5$ min. In allocating specific operation to a machine within a process group, a rounded uniform distribution function was used. Task loading and unloading times are fixed at 0.5 min each. Finite numbers of input and output machine buffers are used. The first-in first-out dispatching rule is employed for the input and output buffers in prioritizing tasks in queue waiting for (a) processing on a machine and (b) transportation.
- Robot specification
  Multiple loading capacity robots are deployed for material handling purpose. For standardization purpose, loading capacity is based on the number of pallets regardless of the actual unit size of a material. The number of robots, v, in the system is known. Robots' velocity is constant at 40 m/min. The travel paths connecting the processing machines are bidirectional. There is no other material handling medium used. All machines and robots are assumed to operate at 100% efficiency.

4.2. Simulation process operators

The simulation experiment is carried out in accordance with the procedure follows here. The first test used to verify the simulation result is called chi-square goodness-of-fit test. Its purpose is to test for distributional adequacy. The chi-square test is used to test if a sample of data came from a population with a specific distribution. An attractive feature of the chi-square goodness-of-fit test is that it can be applied to any univariate distribution for which one can calculate the cumulative distribution function. The chi-square goodness-of-fit test is applied to binned data (i.e., data put into classes). This is actually not a restriction because for non-binned data one can simply calculate a histogram or frequency table before generating the chi-square test. However, the values of the chi-square test statistic are dependent on how the data are binned. Another disadvantage of the chi-square test is that it requires a sufficient sample size in order for the chi-square approximation to be valid.

The chi-square goodness-of-fit test can also be applied to discrete distributions such as the binomial and the Poisson rather than continuous ones. The Kolmogorov–Smirnov and Anderson–Darling tests are restricted to continuous distributions.

The chi-square test is defined for the hypothesis:

H_0: The data follow a specified distribution.
H_1: The data do not follow the specified distribution.

Test statistic: For the chi-square goodness-of-fit computation, the data are divided into k bins and the test statistic is defined as

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \tag{1}$$

where O_i is the observed frequency for bin i and E_i is the expected frequency for bin i. The expected frequency is calculated by

$$E_i = N\,(F(Y_u) - F(Y_l)) \tag{2}$$

where F is the cumulative distribution function for the distribution being tested, Y_u is the upper limit for class i, Y_l is the lower limit for class i, and N is the sample size.

This test is not valid for small samples, and if some of the counts are less than five, it is required to combine some bins in the tails. The significance level is α. The test statistic follows, approximately, a chi-square distribution with $(k - c)$ degrees of freedom, where k is the number of non-empty cells and c is the number of estimated parameters (including location and scale parameters and shape parameters) for the distribution $+1$.

For example, for a 3-parameter Weibull distribution, $c = 4$. Therefore, the hypothesis that the data are from a population with the specified distribution is rejected if

$$\chi^2 > \chi^2_{(\alpha,k-c)} \tag{3}$$

where $\chi^2_{(\alpha,k-c)}$ is the chi-square percent point function with $k-c$ degrees of freedom and a significance level of α.

In the above formulas for the critical regions, the convention that χ^2_α is the upper critical value from the chi-square distribution and $\chi^2_{1-\alpha}$ is the lower critical value from the chi-square distribution.

Using the computations, the H_0 hypothesis is accepted while the test statistics is larger than *p*-value, that is, the data follow exponential distribution. The only problem, as described above, is the small number of samples leading to apply another test.

The Kolmogorov–Smirnov test is used to decide if a sample comes from a population with a specific distribution. The Kolmogorov–Smirnov (K–S) test is based on the empirical distribution function (ECDF). Given N ordered data points $Y_1, Y_2, \ldots, Y_N$, the ECDF is defined as

$$E_N = \frac{n(i)}{N} \tag{4}$$

where $n(i)$ is the number of points less than Y_i and the Y_i are ordered from smallest to largest value. This is a step function that increases by $1/N$ at the value of each ordered data point.

An attractive feature of this test is that the distribution of the K–S test statistic itself does not depend on the underlying cumulative distribution function being tested. Another advantage is that it is an exact test (the chi-square goodness-of-fit test depends on an adequate sample size for the approximations to be valid). Despite these advantages, the K–S test has several important limitations.

1. It only applies to continuous distributions.
2. It tends to be more sensitive near the center of the distribution than at the tails.
3. Perhaps the most serious limitation is that the distribution must be fully specified. That is, if location, scale, and shape parameters are estimated from the data, the critical region of the K–S test is no longer valid. It typically must be determined by simulation.

The Kolmogorov–Smirnov test is defined by:

H_0: The data follow a specified distribution.
H_1: The data do not follow the specified distribution.

The Kolmogorov–Smirnov test statistic is defined as:

$$D = \max_{1\le i\le N}\left(F(Y_i) - \frac{i-1}{N}, \frac{i}{N} - F(Y_i)\right) \tag{5}$$

where F is the theoretical cumulative distribution of the distribution being tested which must be a continuous distribution (i.e., no discrete distributions such as the binomial or Poisson), and it must be fully specified (i.e., the location, scale, and shape parameters cannot be estimated from the data).

The significance level is α. The hypothesis regarding the distributional form is rejected if the test statistic, D, is greater than the critical value obtained from the standard table. There are several variations of these tables in the literature that use somewhat different scalings for the K–S test statistic and critical regions. These alternative formulations should be equivalent, but it is necessary to ensure that the test statistic is calculated in a way that is consistent with how the critical values were tabulated.

The following tactical and operational issues have to be addressed in designing the ROBOT system: critical factors and DPs.

4.3. Critical factors and DPs

In this experiment, we consider the robot deadlock, robot conflict free, and throughput.

- Robot deadlock is an important output variable for determining the economic design of the system and its efficiency of operation. In this paper, deadlock represents the percentage of time the vehicles were blocked for attempting to move (e.g., because they were waiting behind a stopped vehicle on the guide-path).
- Robot conflict free is the movement of robot so that no conflicts occur.

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Table V. List of the critical factors.

Notation	Remarks
y_1	Robot deadlock
y_2	Robot conflict free
y_3	STH
y_4	MFT
y_5	ETDT

Table VI. Value and tolerance of the DPs.

DPs		Value	Tolerance
Robot	NOV: x_1	20	10
	CAP: x_2	10	5

- The system throughput (STH) is the amount of finished goods produced by a system over a period of time. It is used to measure the system-wide performance.
- Mean flow time (MFT)—flow time, F_i refers to the time duration required for a job to be completed. Parameters needed to compute F_i include:
  O_{ij}, operation time; tp_{ij}, machine processing time; tt_{ij}, transport time; tu_{ij}, loading/unloading time; tq_{ij}, queuing time,; R_i, job release time; and n, the total number of job processed.

MFT complies with (6)–(9).

$$O_{ij} = tp_{ij} + tt_{ij} + tu_{ij} + tq_{ij} \tag{6}$$

$$C_i = \sum_{i=1}^{n} O_{ij} \tag{7}$$

$$F_i = C_i - R_i \tag{8}$$

$$MFT = \frac{1}{n}\sum_{i=1}^{n} F_i. \tag{9}$$

- Effective total distance travelled (ETDT)—this research used ETDT as an indicator to measure the effectiveness of material transportation. ETDT is defined as the ratio of total distance travelled to STH produced. ETDT was selected because it could represent the robot traveling efficiency with regards to the throughput.

Table V presents the specification of the critical factors that are considered in this study.

The DPs for the simulation design and analysis of cell manufacturing with robots are used for the multifactorial analysis and the simulation-based optimization. DPs refer to the controllable input factors that are contemplated during the development of a robot system. The study starts with experimenting two DPs: (i) the number of robots (NOV) and (ii) robot loading capacity (CAP).The experimental design includes two DPs. To separate the changed and fixed parameters, sensitivity analysis is used for the DPs. Table VI presents the value and error of the DPs for the sensitivity analysis.

4.4. *Simulation analysis*

Simulation has been carried out by testing all of the combination of experimental factors over 8-h production time using ARENA 15 simulation software package. Analysis had been carried out with the intention to determine the performance of multiple robots. The outcomes of the performance indicators are analyzed.

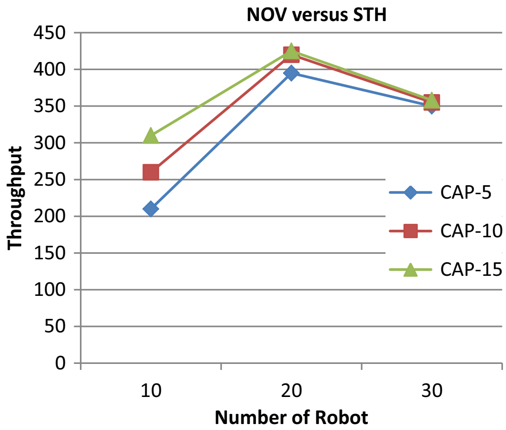

Fig. 4. Simulation result for STH comparison.

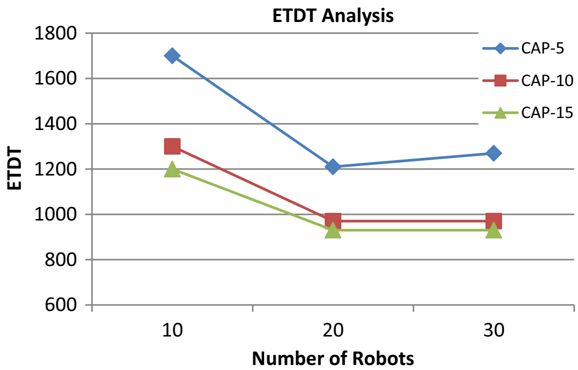

Fig. 5. Simulation results for effective total travel distance.

Deployment of different robot loading capacity resulted in different STH outcomes. The result in Fig. 4 shows that deployment of robot with different loading capacity resulted in significant throughput outcomes particularly for smaller NOV category. On the other hand, the differences are less when 20 robots are deployed. There is also a decreasing trend of throughput specifically when the number of vehicles deployed is too high.

In addition, the ETDT data for each robot were also analyzed. Generally, ETDT values drop when the quantity of robots is increased. Besides, there is also significant improvement of ETDT particularly when robots with higher loading capacity are utilized. The result depicts that robot categories with 10 and 15 capacities consistently have better ETDT compared to robot with 5 capacities. The result is depicted in Fig. 5.

Moreover, MFT of the work-in-process materials has also been studied. The result illustrated in Fig. 6 shows that generally, the MFT decreases when the NOV increases up to a certain number of robots. Then, MFT starts to increase back. This simply highlights the need to identify optimal design variables when MTS is to be established. The result also shows that utilizing robot with higher loading capacity could improve the MFT outcome compared with robot with lower loading capacity.

To support the discussion, we also carried out analysis of variance (ANOVA) on the simulation data obtained. The result is depicted in Table VII. Based on the ANOVA conducted with a significance level of 5%, the main effects and corresponding curvature were proved to be significant on various critical factors.

5. Comparative Study

As explained and detailed in Section 4.4, the simulation study for the performance analysis of the robotic cell manufacturing system was reported. To have a comparative study, one could make use of another simulation environment and investigate the differences. Thus, the proposed simulation model is implemented in the Simula8 environment.

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Table VII. ANOVA for the critical factors and DPs (significant effects at the 5% level).

DP	Critical factor	Sum of square	Degrees of freedom	Mean square	F value	$Pr > F$	R^2
NOV	Robot deadlock	23994.701	2	1713.907	93.802	0.00	0.916
	Robot conflict free	0.291	2	0.021	95.234	0.00	0.917
	STH	31,358	2	15,679	16.03	0.004	0.841
	MFT	4529	2	2265	11.66	0.009	0.803
	ETDT	166,117	2	83,059	1.23	0.356	0.782
CAP	Robot deadlock	25732.452	2	1516.306	91.504	0.00	0.911
	Robot conflict free	0.18	2	0.033	93.123	0.00	0.923
	STH	3692	2	1846	0.33	0.531	0.825
	MFT	1020	2	510	0.65	0.553	0.815
	ETDT	376,349	2	188,175	5.82	0.039	0.796

Table VIII. Results of different simulation software.

Contents	Simul8	ARENA
y_1	22.44	20.8
y_2	0.548	0.551
y_3	478	508
y_4	124	110
y_5	910	807
x_1	25	22
x_2	12	14

Confidence level = 95%

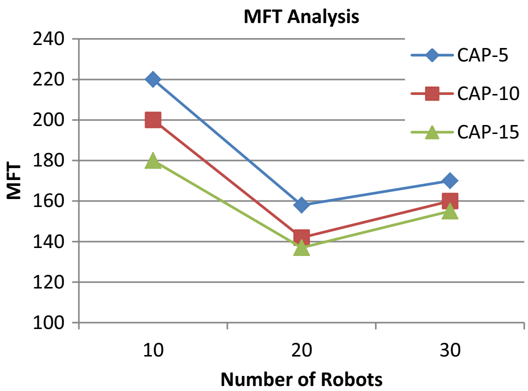

Fig. 6. Simulation analysis for MFT.

As shown in Table VIII, generally ARENA performs better than Simul8. But, several factors could influence the results of the simulation. For more comprehensive comparisons considering uncertainty of operational factor in real industrial cases, the analytical method is used. Data envelopment analysis (DEA) is proposed and modified for the comparison purpose follows here.

5.1. Data envelopment analysis

DEA is a method for obtaining the relative efficiency of a single decision maker, decision-making unit (DMU), in that it compares it with the linear combinations involved with other DMUs. Decision-making units are homogeneous units with the same inputs and outputs. Performance measurement has always been a concern for researchers due to its importance in evaluating the performance of an organization. Among the existing approaches, DEA is one of the most desirable models that are used in multiresponse optimization problems. DEA is a fractional mathematical programming method for measuring the relative efficiency of a set of competitive and homogeneous DMUs in which multiple

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inputs and multiple outputs exist.[20] DEA application areas have expanded rapidly in recent decades. Model (10) shows a Charnes, Cooper and Rhodes (CCR) enclosure model of the axle input.[21,22]

$$
\begin{aligned}
&\min y_0 = \theta \\
&\text{s.t.}: \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0} \quad (r = 1, 2, \ldots, s) \\
&\sum_{j=1}^{n} \lambda_j y_{rj} x_{ij} \leq \theta x_{i0} \quad (i = 1, 2, \ldots, m) \\
&\lambda_j \geq 0, \theta : Free
\end{aligned} \tag{10}
$$

In this paper, we use a non-decreasing return-to-scale axis input model and environmental factors that are defined as follows (11):

$$
\begin{aligned}
&\min Z_0 = \theta - \sum_{i=1}^{2} \varepsilon.Sn_i - \sum_{r=1}^{3} \varepsilon.Sp_r \\
&\text{s.t.}: \\
&\sum_{j=1}^{9} y_{rj}\lambda_j - Sp_r = y_{r_0} \qquad r = 1, \ldots, 5. \\
&\sum_{j=1}^{9} x_{ij}\lambda_j + Sn_i - \theta.x_{i_0} = 0 \qquad i = 1, 2, 3. \\
&\sum_{j=1}^{9} E_{lj}\lambda_j - \theta.E_{l_0} \leq 0 \qquad l = 1, \ldots, 10. \\
&\sum_{j=1}^{9} \lambda_j \geq 1 \\
&\lambda_j, Sp_r, Sn_i \geq 0, \theta : Free
\end{aligned} \tag{11}
$$

5.2. *Robust data envelopment analysis*

In most real-world environments, we often try to describe a manufacturing system design problem, whose parameters are not known before. We need to take this uncertainty into account when configuring a simulation model. In a true decision process, we often encounter a combination of uncertainty, including local and structural uncertainty. We can define a range of possible or sometimes probabilistic or probabilistic distributions for managing uncertainty. Fazli-Khalaf et al.[21] described a method of the robust stochastic fuzzy rule that uses fuzzy numbers of triangular LRs and, under the combined uncertainty, with a probability average and a fuzzy scenario, they considered three aspects:

1. the average probable value of the objective function's weight;
2. possible changeability;
3. the goal function scenario changes.

That incorporates average costs, desirable stability, and reliability in this method. The proposed model by Fazli-Khalaf et al.[21] is presented as follows:

$$
\begin{aligned}
\min Z = &\left[\frac{C^{(1)} + C^{(2)} + C^{(3)}}{3}\right] x + \sum_{s} P_s \left[\frac{d^{(1)} + d^{(2)} + d^{(3)}}{3}\right] y_s + \beta \sum_{s} P_s \left[\left(\left[\frac{d^{(1)} + d^{(2)} + d^{(3)}}{3}\right] y_s \right.\right. \\
&\left.\left. - \sum_{s'} P_{s'} \left[\frac{d^{(1)} + d^{(2)} + d^{(3)}}{3}\right] y_{s'}\right) + 2\theta_s\right] + \sum_{s} \delta \varepsilon_s
\end{aligned} \tag{12}
$$

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s.t.

$$Ax \leq \left[(2\alpha - 1)\, b^{(1)} + (2 - 2\alpha)\, b^{(2)}\right] \setminus \left[(2\eta - 1) f^{(1)} + (2 - 2\eta) f^{(2)}\right] y_s + \varepsilon_s$$

$$\geq \left[(2\varphi - 1)\, h_s^{(3)} b^{(3)} + (2 - 2\varphi)\, h_s^{(2)}\right] \left[\frac{d^{(1)} + d^{(2)} + d^{(3)}}{3}\right] y_s$$

$$- \sum_s P_s \left[\frac{d^{(1)} + d^{(2)} + d^{(3)}}{3}\right] y_s + \theta_s \geq 0 \qquad \forall s \tag{13}$$

$$x, \varepsilon_s, y_s \geq 0,\ 0.5 < \alpha, \eta, \varphi, \beta \leq 1 \qquad \forall s \tag{14}$$

where parameters c and d in the objective function are regarded as uncertain that has triangular possibility distribution and they are formulated based on the expected value of uncertain parameters. In the equivalent crisp model, it is assumed that uncertain parameter c has the triangular membership function and could be represented as $C = C^{(1)} + C^{(2)} + C^{(3)}$. The objective function is modeled on the basis of average value of uncertain parameters. Parameters d, f, and h_s are regarded as uncertain coefficients of constraints, and they are modeled regarding satisfaction level of uncertain parameters $0.5 < \alpha, \eta, \varphi, \beta \leq 1$. In other words, satisfaction level of each uncertain parameter should be determined based on preference of company Decision Makers (DMs). Notably, increasing satisfaction level of uncertain parameters would result in risk-averse output decisions of the extended model. The RDEA model of this paper is formulated as follows:

$$\max Z = \theta_{s0} \tag{15}$$

s.t.

$$\sum_s h_s y_{s0} - \theta_{s0} - \sum_s P_s \left[\frac{d^{(1)} + d^{(2)} + d^{(3)}}{3}\right] y_s - (2\varphi - 1)\, h_s^{(3)} b^{(3)} + (2 - 2\varphi)\, h_s^{(2)} \geq 0 \quad \forall s' \tag{16}$$

$$\sum_s f_s y_{s0} - \sum_s P_s \left[\frac{d^{(1)} + d^{(2)} + d^{(3)}}{3}\right] y_s - \left[(2\alpha - 1)\, b^{(1)} + (2 - 2\alpha)\, b^{(2)}\right] \setminus \left[(2\eta - 1) f^{(1)}\right.$$

$$\left. + (2 - 2\eta) f^{(2)}\right] + \varepsilon_s \geq 0 \qquad \forall s' \tag{17}$$

$$x, \varepsilon_s, y_s \geq 0,\ 0.5 < \alpha, \eta, \varphi, \beta \leq 1 \qquad \forall s \tag{18}$$

where f_s and h_s are the rth output for company and y_{s0} and θ_{s0} refer to rth output and efficiency score of DMU underconsideration.

To investigate the efficiency of the simulation environments in 12 random experiments, DEA and RDEA are analyzed as shown in Table IX. However, the uncertainty was considered in the RDEA results and the relative performance scores were calculated using the usual DEA, too. Therefore, relative performance scores for experiments are recalculated with regard to uncertainty in data, and the results of the DEA and RDEA models are presented in Table IX.

As shown in Table IX, for Simul8 software, three experiments have 100% performance measures, which are the optimal setting of simulation design of the proposed robotic cell manufacturing system. Using the proposed RDEA model, performance scores are calculated and only one of the experiments has a score higher than 0.9 showing the impact of uncertainty on the optimal simulation configuration. For ARENA, there are three completely efficient settings in DEA, but two experiments with higher than 0.9 score. This implies better performance of ARENA in handling uncertainty of the manufacturing systems.

6. Discussions and Concluding Remarks

Decision makers and experts in the advanced manufacturing systems prefer to have a predicted model before real implementation due to large amount of investment in these systems. One way is to make use of the simulation model. Different simulation software and different simulation setting influence the results. The concept of turning point is an effective strategy to increase the critical factor performance. Given the uncertainty in the data, the typical DEA method is uncertain and may help to make

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Table IX. Comparison the simulation software.

	Simul8		ARENA	
Experiments	**DEA**	**RDEA**	**DEA**	**RDEA**
1	96.63	83.99	100	83.95
2	98.46	80.85	99.96	85.92
3	100	85.35	99.82	85.52
4	96.03	85.33	99.11	85.51
5	97.90	84.57	99.97	94.36
6	100	85.56	98.43	76.08
7	95.63	85.64	98.96	75.37
8	97.63	89.10	97.63	78.85
9	100	83.95	100	84.25
10	98.22	94.36	98.55	87.15
11	98.96	83.67	99.23	94.36
12	99.18	85.10	100	85.33

a mistake. After applying RDEA, the results of the proposed method are shown to be more efficient in ARENA simulation software.

The need for efficiency in the manufacturing industry has never been greater, with material, transportation, and labor costs continuing to rise each year. Successful companies need to ensure that the costs associated with time, equipment, and investments are being considered and optimized. At its core, manufacturing simulation is an inexpensive, risk-free way to test anything from simple revisions to complete redesigns, always with the purpose of meeting production goals at the lowest possible cost. Simulation also provides a means to test and implement principles of lean manufacturing and Six Sigma. And unlike spreadsheet-based analysis and forecasting, manufacturing simulation offers a quick and efficient means to adjust parameters and re-simulate, saving valuable time and hastening results.

References

1. L. Gould, "AGVs in America: An inside look," *Mod. Mater. Handling* **45**(10), 56–60 (1990).
2. B. Sezen, "Modeling automated guided vehicle systems in material handling," *Dogus Üniversitesi Dergisi* **4**(2), 207–216 (2003).
3. H. Fazlollahtabar and M. Saidi-Mehrabad, *Autonomous Guided Vehicles: Methods and Models for Optimal Path Planning* (Springer International Publishing, Cham, 2015). ISBN 978-3-319-14746-8.
4. H. Fazlollahtabar and M. Saidi-Mehrabad, "Methodologies to optimize automated guided vehicle scheduling and routing problems: A review study," *J. Intell. Robot. Syst.* **77**, 525–545 (2015a).
5. H. E. Nouri, O. B. Driss and K. Ghédira, "A Classification Schema for the Job Shop Scheduling Problem with Transportation Resources: State-of-the-Art Review," **In**: *Artificial Intelligence Perspectives in Intelligent Systems. Advances in Intelligent Systems and Computing* (R. Silhavy, R. Senkerik, Z. Oplatkova, P. Silhavy and Z. Prokopova, eds.), vol. 464 (Springer, Cham, 2016).
6. J. Luo, Y. Wu and A. B. Mendes, "Modelling of integrated vehicle scheduling and container storage problems in unloading process at an automated container terminal," *Comput. Ind. Eng.* **94**, 32–44 (2016).
7. E. Cardarelli, V. Digani, L. Sabattini, C. Secchi and C. Fantuzzi, "Cooperative cloud robotics architecture for the coordination of multi-AGV systems in industrial warehouses," *Mechatronics* **45**, 1–13 (2017).
8. I. F. A. Vis, "Survey of research in the design and control of automated guided vehicle systems," *Eur. J. Oper. Res.* **170**(3), 677–709 (2006).
9. I. F. A. Vis, R. D. Koster, K. J. Roodbergen and L. W. P. Peeters, "Determination of the number of AGVs required at a semiautomated container terminal," *J. Oper. Res. Soc.* **52**, 409–417 (2001).
10. R. Arifin and P. J. Egbelu, "Determination of vehicle requirements in automated guided vehicle systems: A statistical approach," *Prod. Planning Control* **11**(3), 25870 (2000).
11. J. Varagul and T. Ito, "Simulation of detecting function object for AGV using computer vision with neural network," *Procedia. Comput. Sci.* **96**, 159–168 (2016).
12. D. Antakly, J. J. Loiseau and R. Abbou, "A temporised conflict-free routing policy for AGVs," *IFAC-PapersOnLine* **50**(1), 11169–11174 (2017).
13. P. Valmiki, A. Simha Reddy, G. Panchakarla, K. Kumar, R. Purohit and A. Suhane, "A study on simulation methods for AGV fleet size estimation in a flexible manufacturing system," *Mater. Today Proc.* **5**(2–1), 3994–3999 (2018).
14. J. M. A. Tanchoco, *Material Flow Systems in Manufacturing* (Chapman & Hall, London, 1994).
15. A. Gupta, K. Singh and R. Verma, "A critical study and comparison of manufacturing simulation software using analytic hierarchy process," *J. Eng. Sci. Technol.* **5**(1), 108–129 (2010).

16. B. Manup and P. Raja, "Collision-avoidance for mobile robots using region of certainty: a predictive approach," *J. Eng. Sci. Technol.* **11**(1), 18–28 (2016).
17. I. Um, H. Cheon and H. Lee, "The simulation design and analysis of a Flexible Manufacturing System with Automated Guided Vehicle System," *Journal of Manufacturing Systems* **28**(4), 115–122 (2009).
18. J. M. A. Tanchoco, P. J. Egbelu and F. Taghaboni, "Determination of the total number of vehicles in an AGV-based material transport system," *Mater. Flow* **4**, 33–51 (1987).
19. R. L. Ott, *An Introduction to Statistical Methods and Data Analysis* (Dexbury Press, Belmont, 1993).
20. A. Charnes, W. W. Cooper and E. Rhodes, "Measuring the efficiency of decision making units," *Eur. J. Oper. Res.* **2**(6), 429–444 (1978).
21. M. Fazli-Khalaf, A. Mirzazadeh and M. S. Pishvaee, "A robust fuzzy stochastic programming model for the design of a reliable green closed loop supply chain network," *Hum. Ecol. Risk Assess. Int. J.* (2017). doi:10.1080/10807039.2017.1367644.
22. A. Yousefi, "Selecting six sigma project: A comparative study of DEA and LDA techniques," 2008 IEEE International Conference on Industrial Engineering and Engineering Management, Singapore (2008).