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A review of assembly optimisation applications using discrete event simulation

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This article reviews literature on the application of Discrete Event Simulation (DES) and optimisation methods for assembly systems. Data from papers is collated and classified based on application domain, optimisation objective functions, model formulations and optimisation methods. This classification enables the identification of key trends within the research. The most common objective functions applied within studies are time and throughput. In addition, what–if scenario analysis is identified as the most common optimisation method. An increase in the use of hybrid methods for simulation modelling and growing application of Artificial Intelligence methods for multi-objective optimisation of DES models has been noted. These growing trends provide a variety of interesting areas for progress in future research.

Keywords: discrete event simulation; assembly; multi-objective optimisation

1. Introduction

In recent times manufacturing environments have become data rich providing researchers with an opportunity to model and simulate the performance of manufacturing systems (Yang, Bukkapatnam, and Barajas 2013). Automotive, electronics and other general production industries have identified simulation modelling as a method to analyse and improve their manufacturing facilities. Discrete Event Simulation (DES) in particular has been widely applied to model and optimise complex manufacturing systems and assembly lines. DES is particularly well suited for modelling manufacturing systems as DES can explicitly model the variation within manufacturing systems using probability distributions. DES is thus capable of answering key operational questions relating to throughput, resource allocation, utilisation and supply and demand. This information has enabled manufacturers to implement significant and beneficial modifications to their facilities to improve operations in order to meet production targets.

Various literature reviews already exist in the area of DES modelling for manufacturing systems; five of the most relevant review papers were analysed as follows. Nikoukaran and Paul (1999) present a review of software selection methods for manufacturing. Authors cite 42 papers and present software evaluation techniques, criteria for software selection and guidelines. Smith (2003) presents a comprehensive review of 212 papers in the area of simulation for manufacturing design and operation. He classifies the papers based on manufacturing system design, system operation and language or package development. Jahangirian et al. (2010) present a systematic review of a wide range of literature on simulation applications from between 1997 and 2006. The paper provides a much broader picture of the range of applied simulation methods used in manufacturing and business. They conclude that hybrid modelling is an area with a rising profile. More recently Negahban and Smith (2014) performed a review of 290 papers following the classification strategy of Smith (2003). They identify a new category: simulation optimisation and metamodelling. They note that this is an area for potential future research. Alrabghi & Tiwari (2015) provide an up-to-date review of simulation optimisation for maintenance systems. This article, however, investigates the more specific area of DES with optimisation methods applied to assembly systems.

This review article is organised as follows: Section 2 details the research methodology used, Section 3 covers the problem domains within papers studied, Section 4 compares optimisation objectives, Section 5 details model formulations used, Section 6 covers the optimisation methods applied, Section 7 summarises the findings and Section 8 concludes the review.

2. Methodology

The database used to select papers for this review was Scopus. A search was carried out using the keywords '(discrete event simulation) AND (assembly or manufacturing) AND (optimisation or optimization)'. The search returned 368 results; papers which were not assembly related were filtered out of these results. This search method was used as manufacturing and assembly can often be used interchangeably within the literature.

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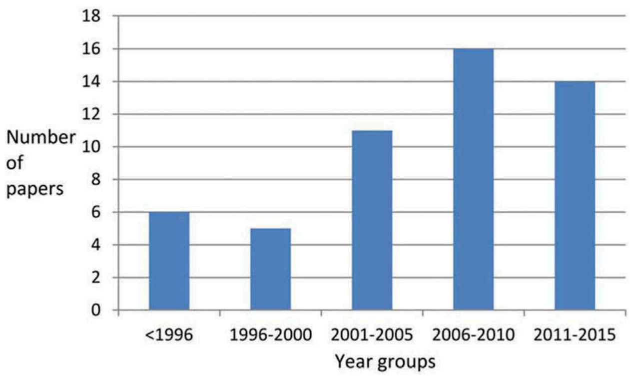

Figure 1. A graph to show the number of papers produced per year group.

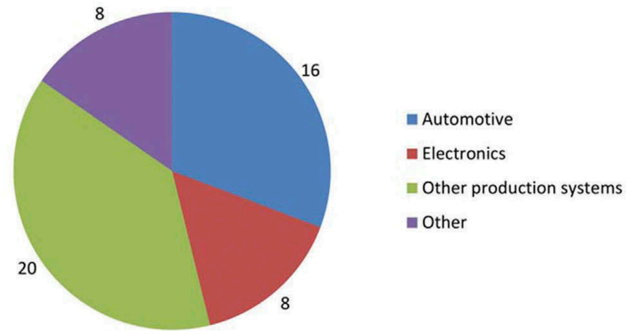

Figure 2. A pie chart to show application domains of papers.

Another further search was made in Scopus using the keywords 'discrete event simulation manufacturing assembly' returning 149 results. This was carried out to find papers that didn't explicitly specify optimisation as a method in the paper. Papers that were not related to assembly systems and optimisation were filtered out. Following both searches, 52 papers were chosen for this review.

Information from the papers was collated into an MS Excel spreadsheet to identify trends in literature and research gaps. Columns within the spreadsheet include: year of paper, paper type (conference or journal paper), application area, simulation software used, model formulation and objective functions among others. From the column 'year' it was seen that the application of DES to assembly systems has received much more interest since 2001; only 6 of the 52 papers studied were from before 1996. The bar chart in Figure 1 illustrates this growing interest.

3. Problem domain

The problem domains of papers studied cover a range of industrial application areas: from small electronics assemblies (Li, Nagarur, and Srihari 2011) to large assemblies such as for the Boeing 747 final assembly (Lu and Sundaram 2002). The application domains for the papers in this review have been categorised as follows: automotive industry, electronics industry, other production systems and other applications. The most common application domain was other production systems; over a third of all papers have been classified as other production systems as shown in Figure 2. The following subsections detail the different problem domains of the papers within this review.

3.1 Automotive industry

Yang, Bukkapatnam, and Barajas (2013) note that the automotive manufacturing environment produces a large amount of data; this provides an ideal opportunity for modelling of these systems using simulation methods.

Authors of research papers within the automotive industry have leveraged the ability of DES to deal with variation, which is inherent within production systems. Ghani, Monfared, and Harrison (2012) use DES to model machining processes in order to monitor energy consumption and they test the method on an assembly production line for an automobile engine block. McDonald, Van Aken, and Ellib (2012) study motor manufacturing for varying demand levels. Baines et al. (2003) perform analysis on worker variation in an assembly line in an automotive plant. Manns and Elmaraghy (2009) consider an automotive manufacturing system with main and side loops and they analyse the different inter arrival times of components.

Studies have been carried out in various parts of the automotive assembly process. Yu et al. (2006) compare sunroof fitting for automobiles using manual and lift-assisted methods. Similarly, Chandra, Huang, and Kumar (2003) analyse the roof and chassis assembly process in an automated car assembly line using LEGO blocks. Martinelli and Valigi (1999) analyse the car dashboard assembly process, which is controlled by a Kanban system. Aguirre et al. (2008) analyse the problem of part manufacturing for the internal combustion engine and Yang, Bukkapatnam, and Barajas (2013) focus on the powertrain manufacturing process.

The control aspects of automobile assembly have been widely considered for optimisation. Ferreira, Gómez, et al. (2012; Ferreira, Ares, et al. 2012) develop a Decision Support System (DSS) for four closed loop automobile assembly and preassembly lines; this is noted to be a typical network configuration within the automotive sector. Steinemann et al. (2013) model the downstream assembly processes for automotive manufacturing to assist the line manager with decision-making. Otamendi (2011) analyses different cell designs to incorporate new tasks into assembly of automobiles. McHaney and Douglas (1997) and Zhao et al. (2010) both consider vehicle assembly and the associated material handling processes.

3.2 Electronics industry

Electronics manufacturing is another area in which a considerable number of papers were found. In particular electronics manufacturing often comprises of mixed model assembly lines incorporating high product variability. Khalil and Stockton (2010) model a low-volume mixed model electronics production environment. DeJong (2001) considers semiconductor manufacturing with different product mix. Mendes et al. (2005) balance a mixed model PC camera assembly line in order to smooth the workload balance between and within workstations. Li et al. (2011) analyse the printed circuit board electronics assembly process and they build a model incorporating the different cycle times for different products. Pradhan and Damodaran (2009) look at Integrated Circuit (IC) manufacturing for optoelectronics assembly with potential failures during testing stages followed by rerouting.

Other features of electronics assembly have been modelled. Stratman, Roth, and Gilland (2004) model the workforce skill level for an electronics manufacturer for the manual assembly of electronic components, whereas Brennan and Rogers (1995) use DES to design a partially automated assembly line. Li, Nikolaidis, and Mourelatos (2011) apply their methodology to assist with understanding the effect of changes on the electronics parts assembly system without using Monte Carlo Simulation methods.

3.3 Other production systems

The most common application area within studies was general production or manufacturing systems. In particular authors often model flexible production systems and then analyse the system for different production scenarios.

Various authors have modelled their flexible assembly systems. Iwata and Oba (1984) build a simulation engine for a flexible manufacturing system and similarly Cave, Nahavandi, and Creighton (2006) consider a stochastic mixed model assembly system. Zeng, Wong, and Leung (2012) model the labour-intensive and complicated apparel sewing manufacturing assembly line; this line is required to be very flexible. They solve the operator allocation problem for this line. Bulgak and Sanders (1991) also consider flexible assembly systems.

The control aspects of production assembly have been modelled by a number of authors. Koulouriotis, Xanthopoulos, and Tourassis (2010) model a four-stage manufacturing line and examine the production control, they note that this is vital for maintaining competitiveness. Ismail et al. (2011) consider a high-volume assembly line for stationary manufacturing and they model the control and physical aspects of the system. Kibira and McLean (2002) also visually model the assembly tasks for workers for a tool production environment. Korytkowski, Wiśniewski, and Rymaszewski (2013) optimise the dispatching rules for a printing production system.

The resource management and material handling have been considered by a number of authors. Hao and Shen (2008) model the production and material handling process for an assembly line in a production environment and Mehrsai et al. (2013) model the logistics for production and then optimise parameters for autonomous objects. Quite differently, Proth et al. (1997) consider the supply chain for an assembly system with inventory control. de Kok and Visschers (1999) analyse the different allocation policies for common components. Neira Dueñas et al. (2007) analyse and optimise control variables for the refrigeration compressor production line. Desmet, Aghezzaf, and Vanmaele (2010) analyse inventory (safety stock) for an assembly system. Kouikoglou (2000) considers resource management for a production network with machines for assembly and disassembly operations.

The design of production systems has also been analysed within studies. Wischnewski and Freund (2004) present a solution for modelling of transportation systems for production environments. Bulgak and Sanders (1991), Liu and Sanders (1988) and Liu and Sanders (1989) analyse different designs for asynchronous flexible assembly systems. In later work, Asil Bulgak (1992) analyses and designs automatic assembly systems and subsequently analyses the trade-off between quality and productivity.

3.4 Other application areas

A range of other application domains have been considered in a number of research papers, particularly in transportation areas. Lee, Shin, and Ryu (2009) consider a panel block assembly shop for a shipyard, while Lu, Petersen, and Storch (2007) model the boiler assembly process for ships. Marsh et al. (2010) consider a bicycle assembly problem. Lu and Sundaram (2002) make the airplane assembly process a moving assembly line. Cochran and Kaylani (2008) optimise the design of a tube shop of an aerospace manufacturer. Hugan (2001) uses DES to model traffic at an automobile plant.

Other application domains include configurations for a computer keyboard assembly cell (Spedding et al. 1998) and large-scale modular construction of an industrial plant (Taghaddos et al. 2010).

4. Objective functions

Among the papers considered in this review there were a range of optimisation objective functions specified by authors. These objective functions have been subcategorised as follows: time-based, cost-based, bottleneck reduction, throughput, resource management, utilisation and other objectives. Figure 3 shows the number of papers which consider each type of objective function and 20

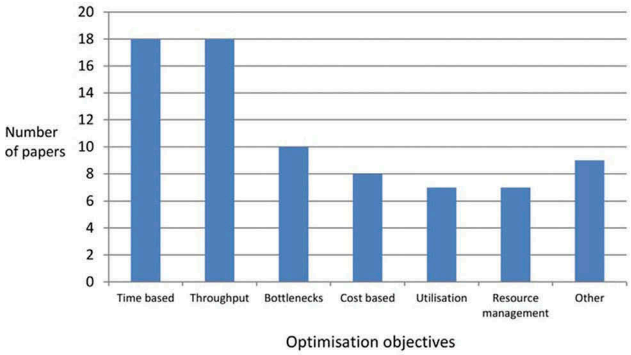

Figure 3. A bar chart to show the number of papers using each objective function type.

papers considered more than one objective function. Some overlap has been noticed between various optimisation objectives; for instance bottleneck reduction will automatically increase the throughput, and the increase in throughput will lead to an increase in sales. Fundamentally many of the objective functions can be interpreted as cost objectives, as they essentially aim to increase the production rate in order to produce more products; this drives sales and increases profit. The following subsections provide more details on each objective function category.

4.1 Time-based

Time-based objectives were the most common amongst all papers studied along with throughput objective functions. This is expected as within competitive manufacturing environments focus is being increasingly placed on implementation of lean initiatives (Steinemann et al. 2013), shortening lead times (Kibira and McLean 2002) and meeting delivery to customers (Li et al. 2011; Proth et al. 1997).

Flow time is defined as the time a job spends in the system; this objective function has been used in several studies. Mehrsai, Thoben, and Karimi (2013) and Mehrsai et al. (2013) consider flow time and makespan (the time difference between start and finish of sequence of tasks) as objectives for minimisation. Korytkowski, Wiśniewski, and Rymaszewski (2013) also consider the mean and maximum flow time, but they also introduce mean and maximum tardiness with the aim to minimise these four objectives. Zeng, Wong, and Leung (2012) consider minimising makespan and maximum flowtime, but they also add minimising the maximum idletime (time when machines have no job to process) as another time-based objective function. Lu and Sundaram (2002), Mendes et al. (2005) and Pradhan and Damodaran (2009) also consider flow time as an objective function.

Li et al. (2011) consider the cycle time variation as the product design changes and they note that most of the machines in the assembly line are controlled with a standard operation time. Kibira and McLean (2002) also consider cycle time and they aim to predict machine cycle time using their modelling method. Desmet, Aghezzaf, and Vanmaele (2010), Lee, Shin, and Ryu (2009), Lu, Petersen, and Storch (2007) and Marsh et al. (2010) consider lead time reduction as an objective and Cochran and Kaylani (2008) implement lead time reduction through a cost function. DeJong (2001) considers on-time delivery performance and Li et al. (2011) aim to minimise the waiting time of parts.

4.2 Throughput

An equally popular optimisation objective function considered among papers is throughput. The average throughput can be defined as the number of final products delivered per time unit (Koulouriotis, Xanthopoulos, and Tourassis 2010). This objective can be linked to profit and cost, as an increase in throughput increases the number of sales; it can also be classified as a time-based objective by definition.

Ferreira, Gómez, et al. (2012), Han et al. (2003), Kouikoglou (2000), Koulouriotis, Xanthopoulos, and Tourassis (2010), Manns and Elmaraghy (2009), Martinelli and Valigi (1999), McHaney and Douglas (1997), Mendes et al. (2005), Spedding et al. (1998) all identify throughput to be an objective function, with many authors considering it to be the primary objective. Yu et al. (2006) and Neira Dueñas et al. (2007) identify productivity as an objective, which is essentially the machine throughput. Ferreira, Gómez, et al. (2012) consider the number of cars produced per hour. Aguirre et al. (2008) consider production volume and likewise Asil Bulgak (1992), Bulgak and Sanders (1991) and Liu and Sanders (1988) consider the expected production rate to be the optimisation objective. Yang, Bukkapatnam, and Barajas (2013) calculate throughput for both their simulation model and their System Dynamics model and they use this performance indicator to perform model validation.

4.3 Bottleneck reduction

Bottleneck reduction is another objective function which is common amongst a number of papers studied. Following the modelling of a manufacturing facility or assembly line this is a clear choice of an objective for simulation modellers. This objective function will enable improvements in throughput and utilisation.

Work In Progress (WIP) is the number of partially finished goods or orders within a given manufacturing system. Aguirre et al. (2008), Koulouriotis, Xanthopoulos, and Tourassis (2010), Li et al. (2011), Otamendi (2011), Pradhan and Damodaran (2009), Yang, Bukkapatnam, and Barajas (2013), Zeng, Wong, and Leung (2012) all aim to minimise WIP. Intuitively this number increases when there are system bottlenecks; hence reduction in WIP has been classified as system bottleneck reduction in this paper. This is agreed by McDonald, Van Aken, and Ellib (2012) who identify potential bottlenecks in their system and note this can reduce performance indicators such as WIP. WIP can also be considered as a cost objective as the partially finished goods represent inventory. Hugan (2001) considers alleviating congestion for a truck plant; this is a similar form of bottleneck reduction. Khalil and Stockton (2010) and Neira Dueñas et al. (2007) consider reducing blockages and this essentially is a form of bottleneck reduction. Steinemann et al. (2013) consider overcoming bottlenecks through available measures such as re-sequencing or adding additional labourers.

4.4 Cost-based

Cost-based objectives are also popular among the papers considered, as these objectives will enable manufacturers to maintain a competitive advantage through cost reduction (Proth et al. 1997). Cost-based functions can be based on minimising cost or maximising profit.

A number of authors consider reducing the costs of production. Marsh et al. (2010) consider the costs of different assembly sequences. Proth et al. (1997) aim to minimise the sum of backlog and inventory costs, while dealing with stochastic demand and yield times. Stratman, Roth, and Gilland (2004) consider production and quality costs, assessing labour, inspection, testing and defect costs. Lu and Sundaram (2002) also consider resource costs, but they add minimising materials which is not considered by Stratman, Roth, and Gilland (2004). Cochran and Kaylani (2008) optimise designs with respect to a cost function; this function also incorporates lead time reduction.

On the other hand, optimisation with respect to profit has been carried out by Koulouriotis, Xanthopoulos, and Tourassis (2010); they consider profit which is formulated based on operation per time unit and also profit from product sale.

4.5 Utilisation

The utilisation of workers and machinery has also been deemed to be an important objective by a number of authors. Cave, Nahavandi, and Creighton (2006) and Mehrsai et al. (2013) use the maximisation of machine utilisation as an objective function. Aguirre et al. (2008) consider utilisation of workers and workstations, whereas Yu et al. (2006) only maximise utilisation of workers. Hugan (2001) aims to maximise the utilisation of an area for a truck plant and Taghaddos et al. (2010) maximise utilisation of yard resources. Utilisation factors have also been considered as objectives by Neira Dueñas et al. (2007).

4.6 Resource management

Another objective used in a number of studies is the management of resources. This objective is linked with cost minimisation as bringing in more labour and materials will incur a cost for the manufacturer.

Zeng, Wong, and Leung (2012) consider minimising the maximum useless productivity of labourers. Mendes et al. (2005) also consider resource utilisation as an objective with the aim that the decision-maker can use this information to fine-tune the configurations of the line. Lu, Petersen, and Storch (2007) minimise materials and resource costs and Steinemann et al. (2013) consider resource optimisation. Aguirre et al. (2008) consider average in process inventory to be a Key Performance Indicator. Ismail et al. (2011) reduce the manpower requirement through system automation and similarly Yu et al. (2006) consider the productivity of manual against assisted fitting operations and they conclude that manual operation increases productivity.

4.7 Other

A number of alternative objectives have been proposed in papers; these include quality, efficiency and availability among others.

Zeng, Wong, and Leung (2012) consider minimising the allocation scheme complexity along with their time-based objectives. Ferreira, Ares, et al. (2012) and Ferreira, Gómez, et al. (2012) consider maximising the performance and system availability and similarly Lu and Sundaram (2002) considers maximising the efficiency. Ghani, Monfared, and Harrison (2012) aim to optimise for energy consumption and they note that reducing the cycle time has an exponential impact on the energy consumption. Asil Bulgak (1992) also considers product quality as an objective and he considers the trade-off between quality and production rate. Taghaddos et al. (2010) use the welfare of society as an objective. Wischnewski and Freund (2004) reduce risk through modelling and visualisation.

5. Model formulation

The authors of studies considered in this review article have formulated models of their manufacturing systems and assembly lines in a number of different ways. All of the studies analysed have modelled their systems using DES, although it has been noted that simulation is labour intensive and time consuming (Kibira and McLean 2002).

In some applications alternative models are formulated and the results are compared to the simulation model; this is often carried out as a validation exercise, as the models are created separately and validated against one another. In other application papers the use of DES models has been coupled with other modelling methods to enable detailed system analysis and optimisation. Among the 52 papers considered within this review, 21 were found to apply only DES, 20 papers coupled DES with other methods such as heuristic rules and analytical approaches and 11 papers were found to compare DES and other modelling methods. This shows significant progress in the field of application of DES modelling through growing integration with other modelling methods. The following subsections outline the papers within each category and the modelling methods used.

5.1 Discrete event simulation

DES models have typically been used to answer specific operations related questions (Yang, Bukkapatnam, and Barajas 2013). The majority of authors have applied commercial DES software to model these systems such as QUEST (Lee, Shin, and Ryu 2009; Lu and Sundaram 2002), Witness (Ghani, Monfared, and Harrison 2012), ProModel (Marsh et al. 2010), Arena (Ferreira, Gómez, et al. 2012) etc.

Arena commercial software suite has been particularly popular amongst studies. It has been used in various assembly applications including: to model a four closed loop network configuration (Ferreira, Ares, et al. 2012; Ferreira, Gómez, et al. 2012), to evaluate different control policies (Koulouriotis, Xanthopoulos, and Tourassis 2010), to validate an aggregated event scheduling method (Zhao et al. 2010), to validate an analytic model (Pradhan and Damodaran 2009), to create a mixed model assembly line (Mendes et al. 2005) and to model a keyboard assembly cell (Spedding et al. 1998).

ProModel software has been used in a number of studies for various modelling tasks including: for modelling of varying assembly sequences (Marsh et al. 2010), for the evaluation of the effect of worker skill dynamics on the cost performance (Stratman, Roth, and Gilland 2004) and for productivity evaluation of manual and automated fitting tasks (Yu et al. 2006).

Another simulation suite QUEST has also been popular among the papers studied. Lee, Shin, and Ryu (2009) use QUEST to assist shop floor decision-making. Lu, Petersen, and Storch (2007) use QUEST to model potential moving line concepts for aircraft assembly and Kibira and McLean (2002) use QUEST to build a DES model, but they also model the manual assembly operations using IGRIP, an ergonomic modeling environment for modeling of manual operations.

Other commercial DES packages include Automod, Witness and Siemens PLM. Hugan (2001) uses Automod to model an automobile truck plant in 3D, Steinemann et al. (2013) use Siemens PLM with a support system called SAMSON to support operational decisions downstream in the production cycle. Ismail et al. (2011) use Witness to create a DES model based on a UML representation. Hao and Shen (2007) use AnyLogic with a hybrid approach combining Discrete Event and agent-based methods for modelling the material handling process.

Various other modelling approaches have been used by authors including: a DES model in C++ to solve an operator allocation problem for hybrid assembly lines (Zeng, Wong, and Leung 2012), development of a simulation software program for flexible manufacturing systems (Iwata and Oba 1984) and a DES program written in Pascal (Asil Bulgak 1992). A number of authors use undisclosed simulation software for instance for the modelling of high-mix low-volume systems (Khalil and Stockton 2010; J. Li et al. 2011).

5.2 Hybrid approaches

Over a third of the papers selected have used simulation modelling in combination with some other modelling technique. These techniques include heuristic methods, mathematical programming formulations and resource planning methods amongst others.

Heuristic rules have been applied within the model formulation by a number of authors. Korytkowski, Wiśniewski, and Rymaszewski (2013) use heuristic dispatching rules within an Arena simulation model. Similarly, Lee, Shin, and Ryu (2009) use heuristic dispatch rules to make initial guesses and they integrate this with a simulation model in QUEST. Mendes et al. (2005) also use heuristics to build initial solutions and the heuristics are then fed into an Arena simulation model. DeJong (2001) applies heuristic methods to assign test problems and then uses Microsoft Visual Basic 6.0 to simulate the different scenarios. Liu and Sanders (1988) apply heuristic modifications to the stochastic quasi-gradient method to find optimal buffer sizes.

Analytical approaches have been applied in combination with simulation models; these include decomposition approaches, mathematical programming and artificial neural network models amongst others. Bulgak and Sanders (1991) use an analytical method to determine the number of pallets for their system and they feed this into their simulation model. Mehrsai et al. (2013) use artificial neural networks, in particular a radial basis function network, to model autonomous objects. Mehrsai et al. (2013) use a linear programing approach with crisp and fuzzy parameters for assisting with operational decisions for autonomous objects. Proth et al. (1997) use a nonlinear programming formulation to model inventory control for a cyclic manufacturing system. Martinelli and Valigi (1999) use a decomposition approach with the simulation model to split the problem into sub-allocation problems. de Kok and Visschers (1999) also use decomposition; their system is decomposed into a number of divergent inventory systems.

Methods have been applied to combine resource planning and material handling with simulation modelling software to enable full system optimisation. Cochran and Kaylani (2008) use manufacturing resource planning and simulation in unison, Neira Dueñas et al. (2007) use Computer Aided Production Planning and simulation simultaneously. Taghaddos et al. (2010) use simulation with Multi Agent Resource Allocation for a modular construction example. Hao and Shen (2007) use AnyLogic with a hybrid approach combining Discrete Event and agent-based methods for modelling the material handling process.

Visualisation methods have also been applied with simulation modelling. Wischnewski and Freund (2004) use visualisation in 3D with simulation modelling to assist decision planners. Kibira and McLean (2002) use QUEST to build a DES model, but in addition they model the manual assembly operations using IGRIP.

5.3 *Comparison approaches*

(Pradhan and Damodaran 2009) note that developing, validating and verifying simulation models is time consuming and computationally costly; analytical models can be a good alternative and easier to solve if the error between the models is insignificant. It is for these reasons that a significant proportion of papers have created alternative models and compared them to simulation models.

Analytic models have mainly been used for comparison to DES models. Manns and Elmaraghy (2009) present a deterministic analytical model for inter arrival times at a bottleneck station. Han et al. (2003) note that their analytical model is unable to handle time-related constraints, which can be achieved by a DES model. Yang, Bukkapatnam, and Barajas (2013) formulate the multistage assembly line problem using both System Dynamics and a DES model. Pradhan and Damodaran (2009) derive equations based on queuing networks with non-Poisson arrival process and non–exponential service time distribution for an analytical model of an assembly line. They use the DES model to validate the analytical derived model. Zhao et al. (2010) use an Arena simulation model to validate an aggregated event scheduling method and similarly Pradhan and Damodaran (2009) use a model in Arena to validate an analytic model.

Other modelling methods have been used for comparison with DES models; these include normal approximation methods and regression models. Li et al. (2011) propose a new method based on Probabilistic Reanalysis to replace time consuming Monte Carlo Simulation runs. Similarly, Liu and Sanders (1989) create a system of equations as an approximation of the Monte Carlo Simulation method and they show that the method compares well to Monte Carlo Simulation. Desmet, Aghezzaf, and Vanmaele (2010) compare simulation models with a new proposed normal approximation model method. McHaney and Douglas (1997) create a meta-model of a simulation model using a full factorial Design of Experiments and they use the results to create a linear regression model. This regression model is shown to accurately reflect the simulation model with less than 5% error.

6. Optimisation methodology

This review article focusses in particular on the use of optimisation methods applied to the simulation of assembly systems. Studies analysed in this review were split into five different categories based on the optimisation methods applied by authors. The number of papers in each category is shown in Figure 4. The most common optimisation strategy is the use of what–if scenario analysis to compare different combinations of input variables and to assess their influence on the chosen output parameters. Other optimisation strategies include manual optimisation, artificial intelligence algorithms, other algorithms and papers that do not perform optimisation and focus only on modelling. Details of each of these optimisation strategies are given in the following sub-sections.

6.1 *What–if scenarios*

The most common method of optimisation among papers studied was using what–if scenario analysis. Figure 4 indicates that in over a quarter of the papers studied the authors applied what–if scenario analysis as the method of optimisation. A number of authors propose analytic and

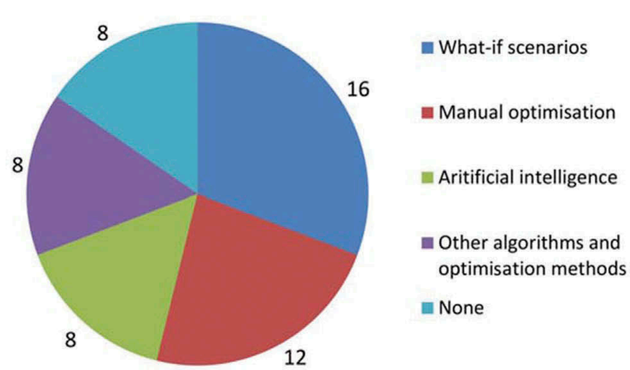

Figure 4. A pie chart to show the number of papers applying each optimisation method.

simulation models and they run these models with different parameter scenarios or introduce changes to the models in order to optimise the system.

Authors have largely used scenario analysis to analyse and determine the effect of different parameter configurations on production and demand scenarios. Ghani, Monfared, and Harrison (2012) run their model with two different production scenarios, the second production scenario being a what–if scenario for demand increase. Koulouriotis, Xanthopoulos, and Tourassis (2010) examine two different demand scenarios and six different control policies. McDonald, Van Aken, and Ellib (2012) also use their DES model with various what–if demand scenarios in order to identify bottlenecks and to ascertain if the system is ready to deal with the expected increase in demand. Mendes et al. (2005) test five different demand scenarios and the results indicate that for two demand scenarios the required production levels could be met. Lu, Petersen, and Storch (2007) simulate three different scenarios with different selection percentages at each decision point representing major design changes. Results are compared for different demand patterns. Ferreira, Gómez, et al. (2012) compare the results of the simulation model output with different values of an external input parameter. The impact of the number of pallets in the first closed-loop on the production rate is also considered. Aguirre et al. (2008) first analyse the possible bottlenecks of the system and then identify the critical processes. Alternative scenarios are then created based on increased capacity, resources and machines; the modification of operation rules is used to identify significant factors. de Kok and Visschers (1999) analyse different allocation policies and find that pre allocation policies perform well with respect to cost and service target levels.

Design of experiments has been used as a more systematic method for performing parameter studies by a number of authors. Authors can use different experimental designs to perform analysis on a variety of different input parameter combinations to assess the effect on output parameters. Khalil and Stockton (2010) design a series of experiments with varying cycle times between machines and they formulate the relationship between these times and blocking and waiting. They test these relationships with estimations and they show less than 5% error in estimations. McHaney and Douglas (1997) also use Design of Experiments to create a linear regression model of a simulation model to speed up the evaluation process. Stratman, Roth, and Gilland (2004) create a full factorial experimental design with 16 different simulation experiments. It is found that 60% of variable manufacturing costs for the temporary worker pool are due to learning and forgetting. Spedding et al. (1998) use a full factorial design of experiments to identify the best buffer and pallet sizes for maximisation of the throughput.

Two authors have performed comparative studies to understand the effect of the assembly sequence on the performance indicators. Li et al. (2011) make a comparative study of two different assembly scenarios concluding that the product design has a dramatic effect on the cycle time. Marsh et al. (2010) use their DES model and linked cost model to analyse the effects of different assembly sequences on the cost. Simulation results indicate that the different assembly sequences have little effect on the average cost per product and cost per operation, but that they have a large effect on the cost of inventory.

Labour scenarios have also been analysed using what–if analysis. Lu, Petersen, and Storch (2007) produced various labour scenarios. Authors analyse the logistics of the stand movement and combine jobs which would require the similar stands; they were able to identify an optimum solution from these scenarios. Yu et al. (2006) also compare manual against assisted operations, also finding that the assisted method yields are preferable as they lead to better productivity.

Authors have also used simulation to model and compare various other scenarios. Mehrsai et al. (2013) present two different scenarios for autonomous objects: a decentralised system and a system with a universal network for all stations; the latter is shown to perform better under test runs. Pradhan and Damodaran (2009) use a simulation model in Arena and 25 different instances to measure the accuracy of the analytical estimates of the performance indicators. Results show that error depends on a number of factors including traffic intensity, product yields, number of nodes and number of shared nodes. Asil Bulgak (1992) analyses the impact of including product quality considerations in the analysis and design of Automated Assembly Systems; he concludes that the quality and inspection procedures should be specified as design parameters to enable full optimisation. Otamendi (2011) screens three different cell layout designs for an assembly cell; these designs are compared with respect to the Work In Progress objective function, synchronisation of cycle times and minimisation of investment costs.

6.2 Manual optimisation

Many authors use simulation and analytical models simultaneously to perform manual optimisation. These methods often include the analysis of simulation results and quantification of relationships between variables to allow the manual identification of optimal solutions.

A number of authors have used their simulation results to optimise a number of their simulation outputs using manual methods. Ghani, Monfared, and Harrison (2012) analyse their simulation results and show that there is an exponential relationship between cycle time and energy consumption and they suggest an optimal result from amongst the solutions. Marsh et al. (2010)

run their simulation model a number of times to generate output data and these are used to feed into the cost model. An optimum solution can be seen from the results of the different simulation runs and through manual optimisation. Stratman, Roth, and Gilland (2004) use results from the simulation to deduce that the largest reductions in manufacturing costs are obtained when workers with the highest levels of competence are put upstream in the production process. DeJong (2001) uses a Design of Experiments to compare weekly and daily customer orders. Results indicate that using the daily customer orders results in better On Time Delivery (OTD) performance and that assignment of the test program after the assembly increases the OTD performance indicator. In a different application, Wischnewski and Freund (2004) use their developed tool for the simulation and 3D visualisation of the assembly system; this enables collision detection in the virtual commissioning phase to ensure smooth set-up in real life.

Analytic methods such as equations have been used to assist in manual optimisation. Han et al. (2003) use an analytic method to assign workstations for painting to improve system throughput and reduce set-up times. The system throughput is maximised by a reduction in the number of colour changes. Desmet, Aghezzaf, and Vanmaele (2010) use their normal approximation models to optimise the required safety stock level for maintaining target service levels. Liu and Sanders (1989) develop a system of equations as an approximation method for allocating buffer sizes in order to maximise the expected production rate.

Authors have used simulation results to manually optimise specific parameters. Ferreira, Gómez, et al. (2012) implement a DSS with the view to optimise the production process. They vary the lengths of the buffers and choose values which maximise the production of the line and reduce blockage and starvation. Yu et al. (2006) suggest that a good workstation design should know the trade-off between effect of lifting devices on productivity and lower back problems. They use their simulation model to compare manual sunroof installation with use of a lifting assist device, showing that use of the assisted device can increase productivity. Manns and Elmaraghy (2009) synchronise design parameters to reduce the number of different inter arrival times and increase the output of their simulation model.

6.3 Artificial intelligence methods

In recent years a growing interest has been seen in the use of artificial intelligence (AI) methods for solving optimisation problems. This trend can also be seen in the use of AI methods to optimise manufacturing and assembly systems. AI methods use concepts from nature to guide the optimisation algorithm in the search for optimal solutions. In particular genetic algorithms (GAs) are a popular algorithm amongst studies. Other methods applied include simulated annealing (SA), differential evolution (DE) and artificial neural networks.

Genetic algorithms have been used to optimise system parameters for assembly systems. Korytkowski, Wiśniewski, and Rymaszewski (2013) use a GA coded in VBA with a simulation model in Arena to optimise dispatch rules. The conclusion is that there is no best dispatching rule, but some rules perform better than others for specific requirements. Koulouriotis, Xanthopoulos, and Tourassis (2010) utilise simulation optimisation to choose optimum design parameters using a GA interface with the serial lines and assembly system. They use resampling as a method to deal with the stochastic objective functions. Neira Dueñas et al. (2007) compare a Macroevolutionary method and a GA. The authors demonstrate the benefits of the Macroevolutionary algorithm including visibility of convergence and a reduction in the number of parameters to adjust. Cochran and Kaylani (2008) also use a GA to optimise their model, which includes stochastic DES parameters.

Simulated annealing (SA) has also been applied to optimise output parameters. SA has been developed for application to combinatorial optimisation problems; hence it is an appropriate optimisation algorithm for the problem. Lee, Shin, and Ryu (2009) use dispatching heuristics as a starting point to create solution schedules which are then optimised using the SA algorithm. Similarly, Mendes et al. (2005) use a heuristic initially to create a solution; then SA is used to attempt to improve the number of workstations. Bulgak and Sanders (1991) use a modified SA method and compare the results to the stochastic quasi-gradient method. Statistical test results suggest no difference in the results using both methods; however, it is noted that the SA algorithm cannot be used for the optimisation of large systems because of the slow convergence to the optimal solution.

Other methods such as artificial neural networks and differential evolution have also been applied. Zeng, Wong, and Leung (2012) propose a new PUDDE differential evolution algorithm. They apply this developed methodology to three test cases where one is a factory in Hong Kong; the PUDDE algorithm performs better than GDE in all tests and cases. Mehrsai et al. (2013) use artificial neural networks (Radial Basis Function networks) with a simulation model. They only train weights and suggest that by intelligently training all parameters of ANN better results can be obtained.

6.4 Other algorithms and optimisation methods

A variety of other optimisation algorithms and methods have been proposed within papers. These include exhaustive search algorithms, gradient descent algorithms and response surface methodology.

Gradient descent methods have been particularly popular among studies. Proth et al. (1997) use a powerful stochastic gradient descent algorithm, which minimises a deterministic function between successive updates of a precision index. Results show rapid progression to the optimal solution in early stages of the algorithm. Infinitesimal perturbation analysis (IPA) has been used in studies to enable gradient estimation. Brennan and Rogers (1995) use IPA to calculate gradient estimates for optimisation of an electronics manufacturing line. Kouikoglou (2000) uses simulation with both IPA and the Standard Clock Method (SCM) to enable gradient estimation for the throughput. SCM is used as an alternative for when IPA fails to produce consistent gradient estimates. The steepest descent algorithm is applied with these methods.

Exhaustive search algorithms have also been applied to optimise assembly systems. Li et al. (2011) apply Solver within Microsoft Excel to solve their electronics assembly optimisation problem. The algorithm applied is an exhaustive search algorithm. Their methodology is used to optimise the system performance with budget constraints.

Other algorithms and methods have also been used to perform optimisation. Mehrsai et al. (2013) use a fuzzy optimisation model to solve their nonlinear mathematical modelling formulation. Results show that autonomous objects can be incorporated to perform global optimisation linking decisions at the operational and strategic level. Taghaddos et al. (2010) use the greedy and ascending auction algorithms to optimise yard resource utilisation. The greedy algorithm is shown to produce sub-optimal solutions suggesting that the ascending auction algorithm is the preferred option. Martinelli and Valigi (1999) use a local search algorithm to optimise decomposed sub-problems.

6.5 *No optimisation*

A number of authors only model their chosen manufacturing and assembly systems and validate these analytical and simulation models and do not perform any optimisation on their models. Often analytic models have been proposed as an alternative to simulation models as they require less computation time. Often the actual model will bring benefits through reducing computation time or showing potential benefit for manufacturers. Authors who have not explicitly considered optimisation have suggested their results can lead to optimisation in future research.

Language- and control-based modelling methods have been used to model systems, but these methods often do not consider optimisation. Ismail et al. (2011) create an explicit control structure using UML to automate a high-volume assembly line. The UML structure is used to build a simulation model of the new automated system. Although all efforts are focussed on modelling, the number of operators is reduced by two-thirds for the implemented automated system. Iwata and Oba (1984) develop a simulation engine for a flexible manufacturing system. They also do not consider optimisation.

Many of the authors who focus on modelling suggest how their modelling work can be further utilised to perform optimisation in future research. Li et al. (2011) integrate design information into their simulation model and they suggest that this will enable electronics manufacturing services to optimise resource deployment for specific products. Steinemann et al. (2013) develop a DSS to help downstream operational decisions; initial trials for the operational focus showed promising results where planning engineers and line managers could see the benefit of the proposed tool. Hao and Shen (2007) concentrate on combining agent-based and DES methods to model a flexible pull production line; they suggest that the material handling and arrangement of buffers can be optimised through comparative studies. Baines et al. (2003) perform a data collection exercise to analyse and quantify the variation in human workers skills in an automotive assembly line. This is used to produce probability distributions for the task time of different workers and tasks. It is suggested that the resulting probability distributions can be used as an input into a DES model in further work.

7. Discussion

The detailed analysis of the 52 papers considered in this study has led to the identification of a number of key trends and links within the field of assembly system simulation and optimisation. The key trends and potential areas for exploitation are outlined in this section.

Analysis of the publication year of papers within this study shows that the number of papers in manufacturing and assembly simulation area of research has grown considerably in recent years; this is shown visually in Figure 1. The number of papers has increased since 2001 showing growing interest in this subject area.

The various application domains of papers within this review were examined to assess trends. The most common application domain was for general production systems. The production line is a highly complex system often with stochastic variables, they are required to be flexible and often incorporate a product mix. This makes the job of production planners particularly complicated; hence production systems are well suited to modelling using DES. The automotive industry was the second most popular application domain amongst papers considered. This is a particularly common application area as the car assembly line often has many options (Steinemann et al. 2013), which leads to many different potential scenarios. The electronics manufacturing industry was the third most popular domain; test cases are often mixed product assembly lines which are required to be very flexible (DeJong 2001; Mendes et al. 2005).

A number of common objective functions of simulation modelling and optimisation of assembly systems have been noted. The objective functions have been categorised as cost-based, time-based, utilisation, resource management, bottlenecks, throughput and other objectives. The most popular objective functions among papers studied were the time-based functions and throughput. This suggests manufacturers are keen to streamline their processes and reduce lead time and increase output of their assembly facilities.

The majority of papers within this review were found to use commercial software packages for DES modelling such as Witness (Ghani, Monfared, and Harrison 2012), QUEST (Lee, Shin, and Ryu 2009) and ProModel (Marsh et al. 2010) amongst others. With the wide range of software available, it is unlikely that there is a requirement for further DES software. Other approaches such as mathematical programming approaches and heuristic methods for representation have been applied in unison with simulation modelling. It has been noted that simulation models require expert knowledge to build and are computationally expensive to run. It is for this reason that a number of authors attempt to build analytical models to replace these simulation models. Simulation models were compared to analytical models by 11 of the papers studied. An increasing use of DES in combination with other methods has also been observed. These methods include decomposition approaches (de Kok and Visschers 1999) and analytic methods (Bulgak and Sanders 1991).

Optimisation approaches of the papers within this review have been categorised and analysed. The most widespread approach to optimising simulation models is the use of what–if scenario analysis. Authors have widely used scenario analysis to analyse the effect of different production and demand scenarios, labour scenarios and parameter choices. This scenario analysis enables production planners to reconfigure their facilities efficiently; however, this method does not have the benefits of application of optimisation algorithms. Manual optimisation has been applied by a number of papers. This involves the analysis of results to deduce relationships and trends between variables and to identify optimum values based on specified objective functions. Authors have also used optimisation algorithms to perform optimisation with respect to their key performance indicators and objectives. Artificial intelligence methods such as genetic algorithms and simulated annealing in particular have been applied in various studies (Mehrsai et al. 2013; Mendes et al. 2005; Zeng, Wong, and Leung 2012). Many of these authors have optimised multiple objectives simultaneously using either aggregated approaches to perform single objective optimisation (Cochran and Kaylani 2008) or using explicit multi-objective optimisation (Neira Dueñas et al. 2007). Authors who have concentrated on modelling Discrete Event systems, and who have not performed optimisation, have noted that the next step is to optimise their developed models.

The papers analysed in this review have led to interesting findings and trends which lead to many potential ideas for future research. With regard to the application domain, many papers have studied the assembly process for assembly of transportation such as ships (Lee, Shin, and Ryu 2009) and electronics equipment (Pradhan and Damodaran 2009); however, no papers were found within the power sector. This could be an interesting application domain, as assembly of large-scale products can be complex. For model formulation there are a lot of potential areas for exploitation with the increasing use of hybrid modelling, comparisons between analytic and simulation models and stochastic parameters. The increased use of multi-objective optimisation enabling simultaneous optimisation of multiple conflicting objectives is also an interesting area for future research.

8. Conclusions

This review article has analysed studies within the area of DES for assembly optimisation. A number of trends have been identified within the literature such as the growing number of research papers in this field. Time-based and throughput objective functions were the most widely used among the papers studied; these objectives enable reduction in lead time and thus an increase in production and sales. Over a third of the papers considered have used hybrid modelling methods combining simulation and other modelling strategies such as heuristic methods, resource planning and analytical models. The most predominant optimisation strategy was the use of what–if scenario analysis; this enables simulation modellers to perform parameter studies to gauge the effect of input parameter changes on the output variables. The increasing use of a variety of artificial intelligence methods and multi-objective optimisation of simulation models has also been shown. These provide interesting areas of research for the future.

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