Chapter 2
Literature Review

2.1 Introduction

This research focuses on production scheduling in VCIM systems, i.e. developing a comprehensive production scheduling model for VCIM systems and developing a robust optimisation solution method for the complex scheduling problem in the developed model. In this chapter, a comprehensive critical literature review is presented, which includes the development of Computer-Integrated Manufacturing, development of Virtual Enterprise, development of Virtual Computer-Integrated Manufacturing, production scheduling issues in VCIM systems, development of optimisation methods, development of Genetic Algorithms, and current research gaps.

2.2 Computer-Integrated Manufacturing

Computer-Integrated Manufacturing (CIM), initially and conceptually coined by Harrington (1973), is a manufacturing system in which computers are used to control the production processes. All functional areas in the system such as design, planning, analysis, purchasing, inventory control, cost accounting, production, marketing, material handling, distribution, management, etc. are linked together by means of computer systems. Therefore, the manufacturing can be automated, faster and less error-prone (Miller et al. 2010). Effective integration of advanced manufacturing technologies such as Computer Aided Design (CAD), Computer Numerical Control (CNC), Computer Aided Process Planning (CAPP), Automated Material Handling Systems (AMHS), Flexible Manufacturing Systems (FMS), etc. in various functional units makes CIM systems powerful (Nagalingam and Lin 1999).

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CIM systems are powerful but very expensive. It is very challenging to justify CIM investments because the benefits and costs associated CIM systems are difficult to quantify. To deal with the challenge, Nagalingam (1999) proposed a so called *innovative decision support system for CIM justification* in which a multi-objective approach, a cost value method to evaluate intangibles, a method to determine the effect of inter-functional benefits of different technologies and a goal programming resource allocation procedure were developed. This decision support system, a multi-attribute decision-making mechanism that accounts for both quantitative and qualitative factors, is capable of helping decision makers make a better CIM investment decision. Nevertheless, uncertainties or stochastic parameters were not taken into account there.

CIM systems are advanced manufacturing systems capable of producing the products with more complexity, higher degree of accuracy, more efficiency, shorter manufacturing lead-time, smaller inventory level and less cost, compared to the traditional manufacturing systems (Yurdakul 2004). However, CIM systems are very complex due to many advanced manufacturing technologies involved. Selecting CIM technologies that satisfy the constraints faced by the company is not a trivial task. To do so, a combined analytic hierarchy process and goal programming model was developed by Yurdakul (2004). Bozdağ et al. (2003) proposed the fuzzy group-decision making method for selecting the technologies to build a CIM system. In addition, an experimental design approach using TOPSIS method was proposed by Yusuf (2012) to select CIM technologies. Selecting the right technologies plays an important role in the success of CIM systems. However, research on optimisation of CIM technology selection is still very limited.

Once CIM systems have been established, operating them effectively is another challenge. A computer shop floor control model for VCIM systems was developed by Yang et al. (2000). Bal et al. (2008) developed a virtual-reality-based information requirement analysis tool for CIM system implementation. To measure the flexibility of CIM systems, a fuzzy cash flow analysis was proposed by Kahraman et al. (2004). To maximise the performance of CIM systems, Salehi and Moghaddam (2009) developed an innovative process planning method, in which the process planning was divided into preliminary planning and secondary planning, and genetic algorithm was used to search for optimal solutions to the problem. Due to advances in computer science and information technology, CIM systems operate very effectively and are widely used in manufacturing industries (Yu et al. 2015). Nevertheless, a comprehensive research on optimisation associated with CIM system operation is still missing.

CIM systems are much more capable than the traditional manufacturing systems, due to the effective integration of various advanced manufacturing technologies (Nagalingam and Lin 1999). Nevertheless, CIM systems can only exploit the local manufacturing resources and their capability will be limited if the resources are not always available (Wang 2007). To overcome this limitation of CIM systems, more flexible manufacturing systems, i.e. Virtual Enterprise and Virtual Computer-Integrated Manufacturing, have been being developed to help small and medium-size manufacturing enterprises survive and thrive in today's competitive global market. The developments of Virtual Enterprise and Virtual Computer-Integrated Manufacturing will be presented in the following Sections.

2.3 Virtual Enterprise

There has been a significant amount of research focused on Virtual Enterprise since this concept emerged in the early 1990s. There are a number of definitions for Virtual Enterprise concept but the most popular one is as follows: "Virtual Enterprise is a temporary alliance of enterprises that come together to share skills, core competencies and resources in order to better respond to business opportunities" (Camarinha-Matos and Afsarmanesh 1999, p. 4).

Virtual Enterprise is capable of effectively exploiting the competitive advantages of the member enterprises by temporary cooperation and networking. The effective cooperation enables Virtual Enterprise to produce the products with higher quality, lower cost, and shorter lead time (Huang et al. 2002). In addition, collaborative manufacturing is a clear trend nowadays; each company is just one node adding some value to the entire production cycle (Camarinha-Matos and Afsarmanesh 1999). Clearly, temporary collaboration is one of the unique characteristics of Virtual Enterprise. Concept of Virtual Enterprise has become a reality and it is a powerful business solution to many companies worldwide in today's competitive global market (Castro et al. 2013; Mun et al. 2009).

Virtual Enterprise is generally formed as follows. There is an enterprise having a big project in hand. However, this enterprise, called principal enterprise, does not complete the project alone because of several reasons such as limited capability, lack of resources or even just wishing to better use its own core business competence. Therefore, the principal enterprise breaks down the project into a number of sub-projects and selects some of those sub-projects to be completed by itself. And then, the principal enterprise invites other enterprises to tender the rest of the sub-projects. A number of appropriate partner enterprises are selected to complete the sub-projects through bidding. As a result, the co-operation between the principal enterprise and its partners forms Virtual Enterprise that can complete the project on time, with a higher quality standard and lower cost. When the project is finished, this co-operation is dissolved (Crispim and Sousa 2009; Huang et al. 2011; Huang and Fan 2007; Ip et al. 2003; Simona and Raluca 2011; Tao et al. 2010; Wu and Su 2005; Ye 2010; Ye and Li 2009; Zeng et al. 2006; Zhang et al. 2012; Zhao et al. 2008).

Partner selection is a critical issue in the success of Virtual Enterprise. Typically, there are four stages in the life cycle of Virtual Enterprise: *creation*, *operation*, *evolution* and *dissolution* (Wu and Su 2005; Ye 2010; Zhong et al. 2009). The success of Virtual Enterprise depends heavily on the creation stage in which the right partner enterprises should be selected. The partner selection problem in Virtual Enterprise has been attracting a lot of research attention. However, still a lot of works needs to be done to find a comprehensive optimisation solution method for the problem.

In the research by Niu et al. (2012), an Enhanced Ant Colony Optimiser for multi-attribute partner selection in Virtual Enterprise was developed. The candidate partners were evaluated based on both qualitative and quantitative aspects, i.e. cost, time, quality, reputation and risk. Experimental data showed that the Enhanced Ant Colony Optimiser could provide better results in terms of search accuracy and computing time, compared to the original Ant Colony Optimiser. Nevertheless, this selection model is not very comprehensive because of not accommodating uncertainties. In addition, much more benchmark algorithms are required to thoroughly verify the effectiveness of the developed Enhanced Ant Colony Optimiser.

Zhang et al. (2013) developed a green model for partner selection in Virtual Enterprise, in which two green criteria, namely carbon emission and lead content, were considered. To solve the problem in this model, Pareto Genetic Algorithm was developed. With Pareto idea, vector encoding, random selection, two-point crossover and single-point mutation, the Pareto Genetic Algorithm outperformed the two other optimisation algorithms, i.e. Simulated Annealing and Particle Swarm Optimisation. However, uncertainties or stochastic parameters in the green partner selection model were not taken into account yet.

Dao et al. (2014) developed an innovative Genetic Algorithm with unique chromosome representation and modified genetic operators, for partner selection and collaborative transportation scheduling in Virtual Enterprise. Effectiveness of the proposed approach was demonstrated through a comprehensive case study. Again, this is a deterministic partner selection model only since the stochastic parameters were not taken into consideration.

Recently, a stochastic partner selection approach for Virtual Enterprise was proposed by Crispim et al. (2015) where both stochastic and deterministic criteria for the partner selection were taken into account. Chance constraints were used to incorporate stochastic features into the multi-objective partner selection model. Alternative configurations of Virtual Enterprise in business environments with uncertainties were ranked by the chance-constrained method. In addition, multi-objective Tabu Search combined with a 2-Tuple Linguistic Procedure was used to support the selection. The preliminary computational results revealed the effectiveness of the proposed approach. Nevertheless, the optimisation solution method to solve the problem still could be better if more advanced optimisation algorithms like Particle Swarm Optimisation, Cuckoo Search, or Genetic Algorithm are used.

Beside the partner selection, there are a number of research topics in Virtual Enterprise such as enabling technologies, supporting platforms, information infrastructures, and Virtual Enterprise controls (Huang et al. 2002). Significant developments in Virtual Enterprise implementation have been achieved so far. However, the capability of Virtual Enterprise is limited due to boundaries still existed between different enterprises. Based on the developments of Virtual Enterprise and Computer-Integrated Manufacturing, it is believed that these two systems are moving to the next stage, namely Virtual Computer-Integrated Manufacturing (Nagalingam et al. 2007; Wang 2007; Wang et al. 2007). The latest development of Virtual Computer-Integrated Manufacturing will be reviewed in the next Section.

2.4 Virtual Computer-Integrated Manufacturing

Concept of Virtual Computer-Integrated Manufacturing (VCIM) was first introduced in a keynote speech (Lin 1997) in the 4th International Conference on Computer-Integrated Manufacturing in Singapore. In the keynote speech, the latest research trends in Computer-Integrated Manufacturing (CIM) were discussed; and then based on the observation of global market condition and rapid technology development at that time, the author predicted that different CIM systems would be integrated together and this integration would go beyond geographical boundaries. This prediction was a starting point of VCIM concept.

The term, VCIM, was first used by Nagalingam and Lin (1999). It should be noted that the letter "V" in VCIM stands for "Virtual", which was borrowed from the concept of Virtual Enterprise. As mentioned in Sect. 2.3, the concept of Virtual Enterprise has become a reality and it is a powerful business solution to many companies worldwide in today's competitive global market. Based on the developments of CIM systems, technologies, Virtual Enterprise and global market, Nagalingam and Lin (1999) suggested that research should be done to develop a global, flexible and integrated manufacturing system called VCIM. However, the definition of VCIM was not very clear then.

Nagalingam and Lin (2000) defined VCIM as a network of interconnected global CIM systems. This definition has two important characteristics. First, VCIM is an integrated manufacturing system in which all of its units are connected to one another by means of computer networks. Second, VCIM is a global manufacturing system in which its units are distributed locally and/or globally. According to them, building and running a VCIM system require a number of things such as a collaborative framework for remote machining, a communication protocol, an integrated architecture, Internet technology, centralised and localised databases, an autonomous decision-making mechanism, etc. Although the global integration was clearly expressed in the definition of VCIM, the flexibility like the one in Virtual Enterprise was not sufficiently emphasised then.

Wang et al. (2003b) proposed the agent-based approach to study and implement VCIM where argued that the agent-based approach is a suitable approach to study and implement VCIM because VCIM is a distributed and integrated manufacturing system. Agents themselves and their interactions with each other could represent a VCIM system well. The agent-based VCIM model had six types of agents, i.e. administration agent, design agent, engineering service agent, manufacturing agent, marketing agent, and financial agent. All of those agents were connected to one another via the Internet infrastructure. As can be seen, the agent-based VCIM model was quite comprehensive. Nevertheless, how the VCIM system works was not described in their work as a consequence of which they did not evaluate the performance of the agent-based VCIM model.

An implementing architecture for VCIM was discussed by Nagalingam et al. (2003) where they highlighted a number of issues needed to be solved to implement a VCIM system. First, real-time connections among agents of a VCIM system must be established. Second, all agents must have a consistent data format. Third, object-oriented technology and common object request broker architecture are required to bring the different distributed agents together to complete the customer orders. Fourth, a common database must be set up to manage the facilities and resources effectively. However, their VCIM model was still not comprehensive since uncertainties, multiple objective functions and multiple product orders were taken into consideration.

In a later research, Wang et al. (2004) developed a new architecture called a parallel processing multi-agent architecture for VCIM systems which was capable of providing multiple coordinator agents with similar functionality, so that the agents could coordinate the information flow across a VCIM system in a parallel manner. A simulation demonstrated that VCIM systems with the parallel processing multi-agent architecture could operate much more efficiently, compared to systems with the then existing architectures. Nevertheless, much more comprehensive and realistic case studies are required to thoroughly verify the robustness of the parallel processing multi-agent architecture.

In a Ph.D. thesis on developing an agent-based architecture for VCIM systems by Wang (2007), the author argued that VCIM systems would help many SMEs survive and thrive in the highly competitive global market, because VCIM systems are very flexible and capable of exploiting locally and/or globally distributed resources. In a VCIM system, manufacturing resources may belong to different partner enterprises or may be located at different regions; however all partner enterprises are willing to work together in an integrated manner to achieve market share. According to this author, to implement a VCIM system, a number of issues need to be solved such as how to interconnect distributed resources to form an integrated manufacturing system, how to dynamically schedule and organise distributed manufacturing resources as a temporary production system to produce a given product, and how to route information and material flow across a VCIM system. To support VCIM implementation, an agent-based architecture was developed by this author, in which there were three types of agents, namely facilitator agent, customer agent and resource agent. The facilitator agent acts as a coordinator to manage information flow across a VCIM system. The customer agent is to provide graphical user interface for customers to use VCIM services. The resource agent represents the manufacturing functionality in a VCIM system. In addition, the facilitator agent in this architecture is capable of (1) processing product order in a parallel manner and (2) incorporating an algorithm to optimise the resource allocation in a VCIM system. Furthermore, a prototype of the agent-based VCIM architecture was built and some insights of the system were reported. However, performance of the proposed approach was not compared to others; in other words, there was no performance benchmark in that research.

Zhou et al. (2010a, b) developed an agent-based VCIM resource scheduling model for small and medium-size manufacturing enterprises. This model aims to unite and integrate all activities in a network of small and medium-size manufacturing enterprises to share the resources to better respond to the constantly changing business opportunities in today's global market. In this model, manufacturing resources may belong to different partner enterprises or may be located at different regions; however all partner enterprises are willing to work together in an integrated manner as a temporary manufacturing system to fulfil a given customer order. When the order is fulfilled, the temporary manufacturing system will vanish. This temporary cooperation between different manufacturing enterprises makes VCIM systems very flexible in exploiting the distributed resources. It should be noted that this characteristic, namely temporary cooperation, was originated from the concept of Virtual Enterprise. Although the agent-based VCIM resource scheduling model was described in detail, a case study was not conducted there to verify the effectiveness of the model.

The above literature review indicates that VCIM inherits two unique characteristics, i.e. integration and temporary cooperation, from two mature concepts, Computer-Integrated Manufacturing and Virtual Enterprise, respectively. VCIM is a new global manufacturing system, which is very integrated and flexible. In addition, majority of the published research focused on developing the agent-based VCIM models; and several prototypes of VCIM models have been built, though are not comprehensive.

2.5 Production Scheduling in VCIM Systems

Production scheduling is very important in VCIM systems because it will affect the quality, cost, and lead time of products (Dao et al. 2016a). After receiving product orders, the VCIM system decomposes the product orders into a number of components which can be independently produced; and then it does the production scheduling by (1) selecting some component suppliers to produce the required components, (2) selecting some assembly agents to assemble the required products and (3) scheduling the shipments to transport the components and products to the required destinations, so that a temporary VCIM production system can be formed to fulfil the product orders. The whole procedure will be repeated for other product orders. VCIM production scheduling is a very complex problem, which requires a comprehensive production scheduling model and a robust optimisation solution method.

Production scheduling in VCIM systems is not exactly the same as production and/or resource scheduling in various traditional manufacturing systems like flexible robotic manufacturing cells (Batur et al. 2012), flexible robotic assembly cells (Abd et al. 2016), flexible manufacturing system (Cardin et al. 2013), make-to-order manufacturing system (He et al. 2014; Sawik 2007), etc. There are a number of differences between VCIM production scheduling and the traditional production scheduling. First, VCIM production scheduling is an integrated optimisation problem since it has a number of interlinked sub-problems of different natures, namely manufacturing agent selection, assembly agent selection, component shipment scheduling and product shipment scheduling. Second, these sub-problems should be simultaneously solved otherwise the obtained solutions may not be feasible. Third, VCIM production scheduling is a dynamic optimisation problem because the number of manufacturing and assembly agents selected in each solution is variable.

Nagalingam and Lin (2000) developed a VCIM production scheduling model as follows. When customer orders a product, the information will go to the central database. The autonomous decision-making mechanism of the VCIM system is then activated to find the best location (a locally controlled manufacturing system) to produce the requested product. During this decision making process, data is exchanged between the central and local databases. After the final decision is confirmed, the selected locally controlled manufacturing system will produce the product and then ship it to the customer. The whole procedure will be repeated for the next customer order. However they did not mention how the autonomous decision-making mechanism finds the best locally controlled manufacturing system to produce the requested product. This implies that this VCIM production scheduling procedure is too general.

Wang et al. (2003a) developed an agent-based VCIM model in which the production scheduling was done as follows. When receiving a product order, the facilitator agent decomposes the order into a number of sub-tasks and then sends them to the available resource agents. The resource agents analyse the received sub-tasks by using their built-in expert systems before responding to the facilitator agent. After receiving the responses, the facilitator agent selects the most appropriate resource agents to complete the sub-tasks and send them the confirmation messages. Finally, the production schedule is built to fulfil the product order. Obviously, this production scheduling is an optimisation problem as many feasible solutions for producing one product may exist. Selecting the best solution among many feasible ones has never been a trivial task especially for complex large-scale problems. However, such selection, i.e. selecting the most appropriate resource agents to complete the sub-tasks was overlooked here.

In a later research, Wang et al. (2004) proposed the following VCIM production scheduling procedure. The facilitator agent decomposes the received product order into a number of interrelated sub-tasks. For each sub-task, the facilitator agent selects a number of potential resource agents and sends them a request message. When receiving the request to complete the sub-task, if capable, the resource agent will generate a production proposal which contains the cost and completion time. After receiving all production proposals for the sub-task from the selected resource agents, the facilitator agent select the best production schedule for the sub-task, based on the cost and completion time. When the best production schedules for all sub-tasks are selected, the full production schedule for the product order is compiled. Again, the selection procedure here was overlooked. In addition, adding the best production schedules for the sub-tasks may not result in the best full production schedule for the product.

The VCIM production scheduling procedures developed by a group of researchers (Nagalingam et al. 2007; Wang 2007; Wang et al. 2007; Zhou et al. 2010a, b) can be summarised as follows:

Step 1	Decompose the received product orders into a number of parts
Step 2	Select manufacturing agents to produce the decomposed parts in Step 1
Step 3	Select transportation agents to transport the decomposed parts directly from their manufacturing agents to the required assembly agent(s)
Step 4	Form full schedules using decisions in Steps 2–3
Step 5	Find the best full schedule among those in Step 4

As can be seen from Steps 1–5, the above model could provide decision makers with feasible solutions to the VCIM production scheduling problem. However, this scheduling model is not comprehensive because it does not consider collaborative transportation in spite of the fact that VCIM systems have a great potential for collaborative transportation since all agents in a VCIM system are willing to work together in an integrated manner. In addition, this scheduling model is not fully integrated because the full schedules in Step 4 are formed by just combining two fixed sub-schedules in Steps 2–3. Without a fully integrated scheduling model, it is impossible to achieve the global optimal solution.

Backward Network Algorithm was developed by Wang et al. (2007) to select the best VCIM production schedule. The developed Backward Network Algorithm is quite simple to implement and it is capable of handling large-scale problems; nevertheless, its capability of obtaining the global optimal solution is very limited, due to the way it constructs the full schedule from the fixed sub-schedules. Also a Genetic Algorithm was developed by Dao et al. (2012) to optimise the production scheduling in VCIM systems. Nevertheless, the global optimal solution to the VCIM production scheduling problem was yet to be achieved as the production scheduling model was not comprehensive because a number of issues such as multiple product orders, multiple objectives, uncertainties and collaborative transportation were not taken into account.

Transportation cost is a significant part of the total cost of the products because VCIM is a global manufacturing system. To reduce transportation cost, a number of researchers and practitioners have been developing collaborative transportation strategy where two or more carriers or shippers form partnerships to share vehicle capacities as well as delivery tasks (Asawasakulsorn 2009; Chan and Zhang 2011; Dai and Chen 2009; Ergun et al. 2007; Li and Chan 2012; Ozener 2008). It can be seen that collaborative transportation strategy has great a potential application in VCIM systems because all of the resource agents in a VCIM system are willing to work together in a fully integrated manner. However, collaborative transportation scheduling has not been considered in any existing VCIM production scheduling model yet.

As can be seen from the above literature review, currently there are two major limitations in VCIM production scheduling. First, the existing VCIM production scheduling models are not comprehensive because the collaborative shipment scheduling, multiple objectives, multiple product orders, uncertainties are not taken into consideration. Second, the existing optimisation methods for solving the VCIM production scheduling problem are not very robust since all sub-problems are not simultaneously solved. Without simultaneous solution of all sub-problems, it is impossible to achieve the global optimal solution.

2.6 Optimisation Methods

Optimisation is generally referred to as finding the best solution to an optimisation problem. Optimisation is always desirable in many fields such as engineering design, computer science, operations research, economics, computational chemistry, biomedicine, etc. (Coelho et al. 2014; Ng and Li 2014; Wang et al. 2013b). Optimisation methods can be broadly classified into two categories: deterministic methods and stochastic methods (Hanagandi and Nikolaou 1998). Each category has advantages and disadvantages. Deterministic methods are capable of guaranteeing the optimality for certain problems thanks to exploiting some helpful features of the problem structure. However, they may fail when tackling black-box problems, extremely ill-behaved functions or complex large-scale problems, due to the combinatorial explosion issue. Stochastic methods can work with any kind of optimisation problem but they are of weak capability of guaranteeing the optimal solutions. Stochastic methods only provide the optimal solutions with probabilistic guarantee and this probability tends to unity in infinite computing time (Liberti and Kucherenko 2005; Moles et al. 2003). Nevertheless, there is no algorithm capable of solving general optimisation problem with certainty in finite computing time (Boender and Romeijn 1995). These two optimisation solution approaches will be explored further below.

2.6.1 Deterministic Optimisation Methods

Deterministic optimisation methods are capable of guaranteeing the optimal solutions for certain problems thanks to exploiting some helpful features of the problem structure. There are a number of deterministic optimisation methods such as Branch-and-Bound methods, Cutting Plane methods, Primal-Dual Decomposition methods, Outer Approximation methods, Inner Approximation methods, Difference of Convex methods, Reverse Convex methods, Reformulation-Linearization methods, Lipschitzian methods, Trajectory and Homotopy methods, Interval Analysis methods, etc. (Floudas 2000).

Hfaiedh et al. (2015) applied Branch-and-Bound method to solve a single machine scheduling problem with release dates and unavailable machines during a fixed interval. The objective function in the scheduling problem is minimising the maximum delivery time. From the computational complexity theory point of view, this scheduling problem is an NP-hard optimisation problem. In the Branch-and-Bound method, Jackson's pre-emptive algorithm with precedence constraints was used to calculate the lower bound and Schrage's sequence was used to determine the upper bound. The effectiveness of the developed Branch-and-Bound method was verified in a number of numerical examples. Nevertheless, solving complex large-scale optimisation problems with the developed algorithm is not practical because a massive computing time would be required.

Fang et al. (2015) developed an exact approach based on the Cut-and-Solve and Cutting Plane methods for solving the capacitated lane reservation problem with residual capacity. The objective here is to minimise the impact of lane reservation. In this approach, a number of new algorithms were developed to find appropriate valid inequalities to speed up the optimal convergence of the proposed approach. Experimental data showed that the proposed approach outperforms other algorithms and CPLEX solver in the literature. However, a massive computing time would prevent the developed algorithm from solving complex large-scale problems.

Ackooij and Malick (2016) proposed a Primal-Dual Decomposition approach to solve the unit-commitment problem in electricity generation companies. In this research, the two-stage formulation of the unit-commitment problem was first proposed and the Primal-Dual Decomposition approach was then applied to solve it. In the proposed approach, the warm-started bundle algorithms were used and specific knowledge of underlying technical constraints was not required. Performance of the proposed Primal-Dual Decomposition approach was tested in a number of unit-commitment instances. Nevertheless, this is a deterministic problem only since uncertainties were not taken into consideration.

An Outer Approximation method for an integrated problem, called supply chain network design and assembly line balancing with demand uncertainty, was developed by Yolmeh and Salehi (2015) to solve the integrated problem formulated as a mixed integer nonlinear programming. The effectiveness of the developed Outer Approximation method was demonstrated by experimental data. However, multiple objective functions were not considered in their work.

Wozabal (2012) applied the Difference of Convex method to solve the Value-at-Risk constrained Markowitz style portfolio selection problem in financial institutions. This is a non-convex stochastic optimisation problem. A Difference of Convex program was used to reformulate the problem and then a Difference of Convex algorithm was developed to solve it. The robustness of the developed Difference of Convex method was demonstrated in a number of numerical examples. Nevertheless, this is a single objective optimisation method only.

Lan et al. (2016) developed a Branch-and-Reduce method based on Reformulation Linearization technique to solve the regional water supply system planning problem. In this research, a non-convex nonlinear model was formulated. A three-pronged effort associated with the space transformation of decision variables, polyhedral outer approximations and Reformulation Linearisation was used to construct the lower bound. The convergence was accelerated by the Range Reduction method. Efficiency of the proposed approach was verified by numerical results. Again, this planning model is not comprehensive because uncertainty and multi-objective optimisation were taken into consideration.

As can be seen from the above literature review, a number of deterministic optimisation methods have been developed to solve the optimisation problems in various fields such as Supply Chain, Finance, Transportation, Machine Scheduling, etc. which are capable of guaranteeing the global optimal solutions for certain problems thanks to exploiting some helpful features of the problem structure. Nevertheless, deterministic optimisation methods may fail when dealing with black-box problems, extremely ill-behaved functions or complex large-scale problems (Dao et al. 2016b).

2.6.2 Stochastic Optimisation Methods

Stochastic optimisation methods can work with any kind of problem but they have a weak capability of guaranteeing the global optimal solution. Stochastic approaches provide the global optimal solution with probabilistic guarantee only and this probability will become 1 in infinite computing time (Liberti and Kucherenko 2005; Moles et al. 2003). Nevertheless, there is no algorithm capable of finding the global optimal solution with certainty to a general optimisation problem in finite computing time (Boender and Romeijn 1995).

Literature survey conducted in this research shows that stochastic optimisation methods are more popular than deterministic ones in real-life applications. This could be due to a number of reasons. First, stochastic approaches do not require sophisticated mathematical analysis to solve problems. Second, stochastic approaches could handle practical and large-scale problems better than deterministic ones. Finally, nowadays the advanced computational technology allows stochastic approaches to increase the probability of finding the global optimal solution because a large number of solutions can be generated and evaluated in a relatively short computing time (Dao et al. 2016b).

A number of stochastic optimisation methods have been developed to solve many complex large-scale problems such as Tabu Search, Particle Swarm Optimisation, Cuckoo Search, Ant Colony Optimisation, Simulated Annealing, Hill Climbing, Downhill Simplex, Artificial Bee Colony Algorithm, Swarm Intelligence, Differential Evolution Algorithm, Genetic Algorithm, etc. Each method has advantages and disadvantages.

Shahvari and Logendran (2017) developed a Tabu Search algorithm to solve a sequence- and machine-dependent batch scheduling problem in the environment of unrelated-parallel machines. The objective function here is minimising a linear combination of completion time and tardiness. To solve the problem they first developed a mixed integer linear program model, and then a Tabu Search algorithm with multi-level diversification and multi-tabu structure. Experimental data revealed that the developed Tabu Search algorithm outperforms the commercial optimisation software package CPLEX. Nevertheless, this scheduling model is not comprehensive either because it did not include uncertainties and multiple objective functions.

Lin et al. (2016) developed a Particle Swarm Optimisation algorithm for the two-agent multi-facility order scheduling with ready times. In this problem, the total completion time of the orders of one agent was the objective function to be minimised. A Branch-and-Bound algorithm was first proposed to incorporate a number of dominance rules and a lower bound to the problem, and then their Particle Swarm Optimisation algorithm was used to search for the optimal/near-optimal solutions to the problem. In the developed algorithm, a number of techniques such as two-level particle number, neighbourhood improvement, fixed inertia weight and decreasing inertia weight were applied. Efficiency of the proposed Particle Swarm Optimisation algorithm was demonstrated in many case studies.

Majumder and Laha (2016) developed a Discrete Cuckoo Search algorithm to solve a scheduling problem in two-machine robotic cells. The scheduling question here is to determine the sequences of robots and parts in a robotic cell so that the cycle time will be minimised. In the developed algorithm, a fractional scaling factor based method was used to determine the step length of Levy flight distribution. In addition, two neighbourhood search methods, namely Interchange and Cyclical Shift methods, were applied to improve the solution quality. Moreover, a Response Surface Methodology was used to accelerate the convergence of the algorithm. Furthermore, the parameters of the developed algorithm were systematically tuned by Design of Experiment. Effectiveness of the developed Discrete Cuckoo Search algorithm was thoroughly verified in a large number of numerical examples.

Wan et al. (2016) developed a modified Ant Colony Optimisation algorithm combined with Genetic Algorithm to solve the feature selection problem in data mining and pattern recognition. The purpose here is to select the feature subset to maximise the discriminating ability and minimise the redundancy. In this method, there were two models, namely the visibility density model and the pheromone density model. The solution found in the visibility density model was used as the visibility information, while the one in the pheromone density model was used as the initial pheromone information. Robustness of the developed algorithm was compared with a number of existing algorithms in the literature.

Akram et al. (2016) developed a Hybrid Simulated Annealing algorithm to solve the job shop scheduling problem. In the developed algorithm, a fast Simulated Annealing was used for the global search while Quenching technique was used for the local search. In addition, Tabu list was used to avoid revisiting the previously explored solutions. Effectiveness of the developed Hybrid Simulated Annealing algorithm was thoroughly verified in 88 well-known benchmark problems in the literature.

Gao et al. (2016) proposed an Improved Artificial Bee Colony algorithm to deal with the flexible job-shop scheduling problem with fuzzy processing time. Two objective functions, namely minimising the maximum fuzzy completion time and maximising the fuzzy machine workload were considered in this scheduling problem. In the proposed approach, an effective heuristic rule was used to generate the initial population. Robustness of the Improved Artificial Bee Colony algorithm was demonstrated in a number of benchmark problems as well as real-life case studies in remanufacturing industry.

As can be seen from the above literature review, many stochastic optimisation methods have been developed so far and many complex practical optimisation problems in various fields have been solved by the methods. Every algorithm has its own particularities, strengths and weaknesses. Nevertheless, Genetic Algorithm is one of the most popular stochastic optimisation methods, often used to deal with complex large-scale optimisation problems (Marian et al. 2012; Shahlaei et al. 2012). Genetic Algorithm has a number of advantageous characteristics, compared to other stochastic optimisation methods, such as flexibility in defining constraints as well as quality measures, capability of working with both continuous and discrete variables, capability of handling large search space, capability of providing multiple optimal/good solutions, and great potential for applying parallel computing techniques to shorten the processing time (Fahimnia et al. 2008). That is why in this research Genetic Algorithm based approach is chosen to solve the VCIM production scheduling problem. A comprehensive literature review on Genetic Algorithm will be presented in the next Section.

2.7 Genetic Algorithms

Genetic Algorithm (GA) is a popular solution method, often used to optimise solutions to problems in many fields such as engineering, computer science, economic management, supply chain management, etc. (Aguilar-Rivera et al. 2015; Cheng and Chang 2007; Lee et al. 2012; Su et al. 2015). As mentioned in Sect. 2.6, GA has a number of advantageous characteristics compared to other optimisation methods and it is the most suitable tool to solve the VCIM production scheduling problem.

Since being introduced over four decades ago, significant developments in various components of GA such as chromosome encoding (Dao et al. 2014; Dao and Marian 2011c; Zhong and Chen 2002), crossover (Qing-dao-er-ji and Wang 2012; Wang and Zheng 2002), mutation (Tang and Tseng 2013; Wang et al. 2009), evaluation (Chang et al. 2007; Hyun et al. 1998), selection (Stern et al. 2006; Wu et al. 2007) as well as algorithm structure (Dao et al. 2015; Zhou et al. 2011) have been made. These developments make today's GA much more powerful than the traditional GA. It should be noted that GA is a searching philosophy only; there is no standard GA. Generally speaking, when using GA, users must customise some GA components, e.g. chromosome encoding, crossover or mutation. Due to the increasing computing power, application of GA has been expanded to many different fields. It would be interesting to see a big picture of the developments of GA throughout its history. The bibliometrics of GA is presented in the next Section.

2.7.1 Bibliometrics of Genetic Algorithms

To show a big picture of the developments of GA throughout its history, a bibliometric analysis is conducted herein using Scopus database. With the search engine “*Title, Abstract, Keywords*” and with the keywords “Genetic Algorithm” OR “Genetic Algorithms”, 124,799 publications associated with GA published from the beginning of GA history to 2014 were found (accessed on 12 November 2015). The detail of this bibliometric analysis has been published in a journal article (Dao et al. 2017). Some key points from that bibliometric analysis are summarised as follows. Majority of publications associated with GA are in the fields of engineering, computer science and mathematics. Most of the publications are in forms of journal articles and conference papers. The first documents associated with GA were published in 1972. The quantity of the publications has been significantly increasing since 1992 with the average increase rate of 475.7 publications per year.

2.7.2 Latest Developments of Genetic Algorithms

Genetic Algorithm (GA), first introduced by Holland (1975) is a powerful stochastic search algorithm based on the mechanisms of natural genetics and selection (Goldberg 1989). A general description of GA is as follows: “*Genetic algorithm … starts with an initial set of random solutions called population. Each individual in the population is called a chromosome representing a solution to the problem at hand. The chromosomes evolve through successive iterations, called generations. During each generation, the chromosomes are evaluated using some measures of fitness. To create the next generation, new chromosome, called offspring, are formed by either (a) merging two chromosomes from current generation using a crossover operator or (b) modifying a chromosome using a mutation operator. A new generation is formed by (a) selecting, according to the fitness values, some of the parents and offspring and (b) rejecting others so as to keep the population size constant. Fitter chromosomes have higher probabilities of being selected. After several generations, the algorithms converge to the best chromosome, which hopefully represents the optimum or suboptimal solution to the problem*” (Gen and Cheng 1997, pp. 1–2).

The traditional structure of GA is shown in Fig. 2.1. It can be seen that a typical GA has five main components: chromosome encoding, crossover, mutation, evaluation and selection. There have been significant developments in those components such as binary encoding (He and Hui 2010), real encoding (Deep et al. 2009), integer-number encoding with fixed length (Qu et al. 2013), hybrid encoding (Chen et al. 2006), variable length chromosome encoding (Dao and Marian 2011b), multi-dimensional chromosome encoding (Dao et al. 2014), single-point crossover (Dao and Marian 2011a), multi-point crossover (Esen and Koç 2015), heuristic crossover (Balakrishnan et al. 2003), comparison crossover (Maity et al. 2015), hybrid crossover (Suresh et al. 2014), adaptive directed mutation (Tang and Tseng 2013), power mutation (Deep and Thakur 2007), uniform/non-uniform mutation (Michalewicz 1996), single objective evaluation (Faghihi et al. 2014), multi-objective evaluation (Aiello et al. 2013), tournament selection (Castelli and

Vanneschi 2014), roulette-wheel selection (Zhao and Wang 2011), probabilistic selection (Maity et al. 2015), dynamic ranking selection (Boudissa and Bounekhla 2012), etc. Chromosome encoding, crossover, mutation, evaluation as well as selection methods have a certain effect on performance of GA and choosing them is dependent on property of problems under consideration.

Beside the five main components mentioned above, performance of GA is also affected by the algorithm structure. To enhance the search capability of GA, many researchers have attempted to improve the traditional structure of GA as shown in Fig. 2.1 by integrating local search techniques such as Simulated Annealing, Tabu Search, Hill Climbing, Pattern Search, Ant Colony Optimisation, Particle Swarm Optimisation, etc. into GA to create new algorithm called hybrid GA (Akpınar et al. 2013; Mahmoodabadi et al. 2013; Shokouhifar and Jalali 2015a, b; Wang et al. 2013a; Yun et al. 2013). Generally speaking, hybrid GA has better exploitation which is a capability to exploit some promising regions of the search space, compared to traditional GA. However, capability of hybrid GA to explore the search space, so called exploration, is still limited because solutions obtained by hybrid GA are evolved from only one set of solutions, usually, randomly generated in the first generation.

One way to improve the exploration of GA is to increase its population size. Nevertheless, too large population size would make the searching process of GA less efficient. Another way is *multistart* procedure which is simply to run GA for a number of times and the best solution among those achieved in the runs can be considered as the global optimal solution if the number of runs is large enough (Dao et al. 2014; Dao and Marian 2013). However, the existing *multistart* procedure is less capable of exploiting the elite chromosomes from each run as well as balancing between the exploration and exploitation.

Regarding the latest applications of GA in solving the scheduling and/or planning problems, Kundakcı and Kulak (2016) applied GA to solve the dynamic Job Shop scheduling problem. There were a number of dynamic events in the problem such as machine breakdowns, random job arrivals, changes in processing time, etc. Objective function here was to minimise the makespan. To solve the problem, an efficient hybrid GA was developed. Effectiveness of the developed GA was demonstrated in a number of benchmark problems.

Li et al. (2016) developed a Branch Population GA to solve the Dual Resource Constrained Job Shop Scheduling problem. There were two objective functions to be minimised here, i.e. cost and makespan. In the developed GA, the branch population was used to accumulate and transfer the evolutionary experience of parent chromosomes as a result of which population diversity and convergence of the algorithm was enhanced. Two other techniques, i.e. elite evolutionary operator and roulette selection operator based on sector segmentation, were also applied to improve the solution quality. Robustness of the developed Branch Population GA was verified in various numerical examples and case studies.

Xia et al. (2016) developed a hybrid GA with variable neighborhood search to solve the dynamic integrated process planning and scheduling problem. Machine

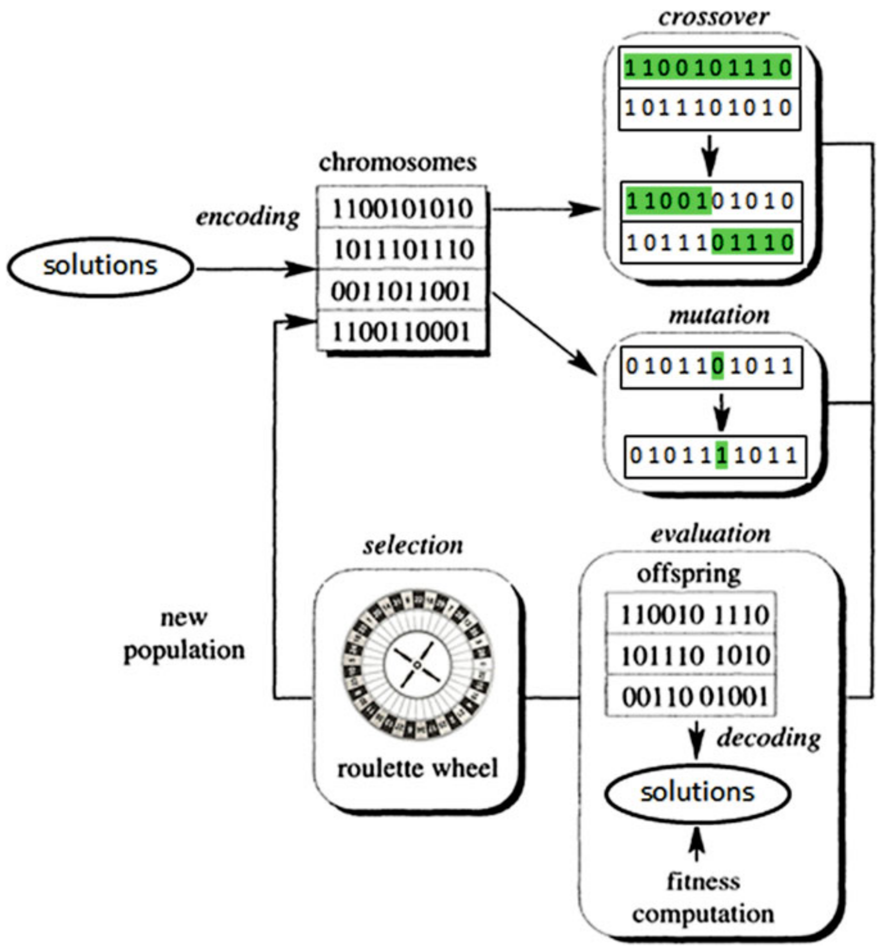

Fig. 2.1 Traditional structure of GA. Adapted from Gen and Cheng (1997, p. 3)

breakdown and new job arrival were two sources of uncertainties in this problem. Through three case studies, they demonstrated the effectiveness of the developed hybrid GA.

Lin and Tsai (2016) developed a deterministic, single objective optimisation algorithm called micro GA to solve the constrained three-dimensional reader network planning problem in the radio frequency identification system. A micro GA with new spatial crossover and correction schemes was developed to solve the problem. Performance of the developed micro GA was compared with Particle Swarm Optimisation algorithm as well as the traditional GA in solving a number of case studies. Experimental data confirmed the effectiveness of the developed micro GA.

Luo et al. (2016) developed a GA to solve an integrated problem of vehicle scheduling and storage location allocation, in container terminal operations. The objective function here was to minimise the berth time of ships. The integrated problem was formulated as a mixed-integer programming model. Experimental data revealed that the developed GA outperforms the commercial software. Again, they did not take uncertainties and multiple objective functions into consideration.

As can be seen from the above literature review, GA has an impressive record and application. A lot of complex real-world problems have been solved by GA. No wonder many versions of GA have been developed and reported in the literature due to the fact that GA is a searching philosophy only; there is no standard GA. Generally speaking, when using GA, users must customise GA components, e.g. chromosome encoding, crossover or mutation to their needs.

2.8 Current Research Gaps

The literature reviewed in Sects. 2.2–2.7 shows that currently there are two major limitations in VCIM production scheduling. First, the existing VCIM production scheduling models are not comprehensive because the collaborative shipment scheduling, multiple objectives, multiple product orders, and uncertainties are not taken into consideration. Second, the existing optimisation methods for solving the VCIM production scheduling problem are not sufficiently robust since not all sub-problems are simultaneously solved. Without simultaneously solving all of the sub-problems, it is impossible to achieve the global optimal solution.

This research aims to overcome these two limitations whose outcome will serve as a foundation towards developing a decision support system capable of helping decision makers to operate VCIM systems more effectively.

2.9 Concluding Remarks

In this chapter, a comprehensive literature review on production scheduling in VCIM systems was presented. The review showed that VCIM is a relatively new global manufacturing system, which has two unique characteristics, i.e. integration and temporary cooperation. Production scheduling is vital to VCIM systems because it affects the quality, cost, and lead time of products. In spite of considerable research in this area, currently there are two major limitations in VCIM production scheduling, i.e. lack of a comprehensive scheduling model and lack of a robust optimisation method. This research aims to overcome these two limitations along with a comprehensive VCIM production scheduling model and a robust Genetic Algorithm.

References

Abd, K., Abhary, K., & Marian, R. (2016). Multi-objective optimisation of dynamic scheduling in robotic flexible assembly cells via fuzzy-based Taguchi approach. *Computers & Industrial Engineering, 99,* 250–259.

Ackooij, W. V., & Malick, J. (2016). Decomposition algorithm for large-scale two-stage unit-commitment. *Annals of Operations Research, 238*(1), 587–613.

Aguilar-Rivera, R., Valenzuela-Rendón, M., & Rodríguez-Ortiz, J. J. (2015). Genetic algorithms and Darwinian approaches in financial applications: A survey. *Expert Systems with Applications, 42*(21), 7684–7697.

Aiello, G., Scalia, L. G., & Enea, M. (2013). A non dominated ranking multi-objective genetic algorithm and electre method for unequal area facility layout problems. *Expert Systems with Applications, 40*(12), 4812–4819.

Akpınar, S., Bayhan, G. M., & Baykasoglu, A. (2013). Hybridizing ant colony optimization via genetic algorithm for mixed-model assembly line balancing problem with sequence dependent setup times between tasks. *Applied Soft Computing, 13*(1), 574–589.

Akram, K., Kamal, K., & Zeb, A. (2016). Fast simulated annealing hybridized with quenching for solving job shop scheduling problem. *Applied Soft Computing, 49,* 510–523.

Asawasakulsorn, A. (2009). Transportation collaboration: Partner selection criteria and IOS design issues for supporting trust. *International Journal of Business and Information, 4*(2), 199–220.

Bal, M., Manesh, H. F., & Hashemipour, M. (2008, April 1). Virtual-reality-based information requirements analysis tool for CIM system implementation: A case study in die-casting industry. *International Journal of Computer Integrated Manufacturing, 21*(3), 231–244.

Balakrishnan, J., Cheng, C. H., Conway, D. G., & Lau, C. M. (2003). A hybrid genetic algorithm for the dynamic plant layout problem. *International Journal of Production Economics, 86*(2), 107–120.

Batur, G. D., Karasan, O. E., & Akturk, M. S. (2012). Multiple part-type scheduling in flexible robotic cells. *International Journal of Production Economics, 135*(2), 726–740.

Boender, C. G. E., & Romeijn, H. E. (1995). Stochastic methods. In R. Horst & P. M. Pardalos (Eds.), *Handbook of global optimization*. Boston: Kluwer Academic Publishers.

Boudissa, E., & Bounekhla, M. (2012). Genetic algorithm with dynamic selection based on quadratic ranking applied to induction machine parameters estimation. *Electric Power Components and Systems, 40*(10), 1089–1104.

Bozdağ, C. E., Kahraman, C., & Ruan, D. (2003). Fuzzy group decision making for selection among computer integrated manufacturing systems. *Computers in Industry, 51*(1), 13–29.

Camarinha-Matos, L. M., & Afsarmanesh, H. (1999). The virtual enterprise concept. In L. M. Camarinha-Matos & H. Afsarmanesh (Eds.), *Infrastructures for virtual enterprises—Networking industrial enterprises* (pp. 3–14). The Netherlands: Kluwer Academic Publishers.

Cardin, O., Mebarki, N., & Pinot, G. (2013). A study of the robustness of the group scheduling method using an emulation of a complex FMS. *International Journal of Production Economics, 146*(1), 199–207.

Castelli, M., & Vanneschi, L. (2014). Genetic algorithm with variable neighborhood search for the optimal allocation of goods in shop shelves. *Operations Research Letters, 42*(5), 355–360.

Castro, H., Putnik, G. D., Shah, V., & Cruz-Cunha, M. M. (2013). A simulation tool and its role in supporting the management of the transformation processes of traditional enterprises into virtual enterprises. *Tékhne, In Press, Corrected Proof.*

Chan, F. T. S., & Zhang, T. (2011). The impact of collaborative transportation management on supply chain performance: A simulation approach. *Expert Systems with Applications, 38*(3), 2319–2329.

Chang, P. C., Hsieh, J. C., & Wang, C. Y. (2007). Adaptive multi-objective genetic algorithms for scheduling of drilling operation in printed circuit board industry. *Applied Soft Computing, 7*(3), 800–806.

Chen, C., Xia, J., Liu, J., & Feng, G. (2006). Nonlinear inversion of potential-field data using a hybrid-encoding genetic algorithm. *Computers & Geosciences, 32*(2), 230–239.

Cheng, B. W., & Chang, C. L. (2007). A study on flowshop scheduling problem combining Taguchi experimental design and genetic algorithm. *Expert Systems with Applications, 32*(2), 415–421.

Coelho, L. D. S., Ayala, H. V. H., & Mariani, V. C. (2014). A self-adaptive chaotic differential evolution algorithm using gamma distribution for unconstrained global optimization. *Applied Mathematics and Computation, 234,* 452–459.

Crispim, J., Rego, N., & Jorge, P. D. S. (2015). Stochastic partner selection for virtual enterprises: A chance-constrained approach. *International Journal of Production Research, 53*(12), 3661–3677.

Crispim, J. A., & Sousa, J. P. D. (2009). Partner selection in virtual enterprises: A multi-criteria decision support approach. *International Journal of Production Research, 47*(17), 4791–4812.

Dai, B., & Chen, H. (2009). Mathematical model and solution approach for collaborative logistics in less than truckload (LTL) transportation. In *International Conference on Computers & Industrial Engineering* (pp. 767–772).

Dao, S.D. & Marian, R. (2011c). Modeling and optimisation of precedence-constrained production sequencing and scheduling using multi-objective genetic algorithm. In *Proceedings of the International Conference of Computational Intelligence and Intelligent Systems*, pp. 1027–1032, 6-8 July, London, U.K.

Dao, S. D., Abhary, K., & Marian, R. (2012). Optimisation of resource scheduling in VCIM systems using genetic algorithm. *International Journal of Advanced Research in Artificial Intelligence, 1*(8), 49–56.

Dao, S. D., Abhary, K., & Marian, R. (2014). Optimisation of partner selection and collaborative transportation scheduling in Virtual Enterprises using GA. *Expert Systems with Applications, 41*(15), 6701–6717.

Dao, S. D., Abhary, K., & Marian, R. (2015). An adaptive restarting genetic algorithm for global optimization. In *Proceedings of the World Congress on Engineering and Computer Science* (pp. 455–459).

Dao, S.D., Abhary, K., Marian, R. (2016a). A stochastic production scheduling model for VCIM systems. *Intelligent Industrial Systems*, 2(1), 85-101.

Dao, S. D., Abhary, K., & Marian, R. (2016b). An improved structure of genetic algorithms for global optimisation. *Progress in Artificial Intelligence, 5*(3), 155–163.

Dao, S. D., Abhary, K., & Marian, R. (2017). A bibliometric analysis of Genetic Algorithms throughout the history. *Computers & Industrial Engineering, 110,* 395–403.

Dao, S. D., & Marian, R. (2011a). Optimisation of precedence-constrained production sequencing and scheduling using genetic algorithms. In *International MultiConference of Engineers and Computer Scientists*.

Dao, S. D., & Marian, R. (2011b). Modeling and optimisation of precedence-constrained production sequencing and scheduling for multiple production lines using genetic algorithm. *Computer Technology and Application., 2*(6), 487–499.

Dao, S. D., & Marian, R. (2013). Genetic algorithms for integrated optimisation of precedence-constrained production sequencing and scheduling. In S.-I. Ao & L. Gelman (Eds.), *Electrical engineering and intelligent systems* (pp. 65–80). New York: Springer.

Deep, K., Singh, K. P., Kansal, M. L., & Mohan, C. (2009). A real coded genetic algorithm for solving integer and mixed integer optimization problems. *Applied Mathematics and Computation, 212*(2), 505–518.

Deep, K., & Thakur, M. (2007). A new mutation operator for real coded genetic algorithms. *Applied Mathematics and Computation, 193*(1), 211–230.

Ergun, Ö., Kuyzu, G., & Savelsbergh, M. (2007). Shipper collaboration. *Computers & Operations Research, 34*(6), 1551–1560.

Esen, İ., & Koç, M. A. (2015). Optimization of a passive vibration absorber for a barrel using the genetic algorithm. *Expert Systems with Applications, 42*(2), 894–905.

Faghihi, V., Reinschmidt, K. F., & Kang, J. H. (2014). Construction scheduling using genetic algorithm based on building information model. *Expert Systems with Applications, 41*(16), 7565–7578.

Fahimnia, B., Luong, L., & Marian, R. (2008). Optimization/simulation modeling of the integrated production-distribution plan: An innovative survey. *WSEAS TRANSACTIONS on Business and Economics, 3*(5), 52–65.

Fang, Y., Chu, F., Mammar, S., & Shi, Q. (2015). A new cut-and-solve and cutting plane combined approach for the capacitated lane reservation problem. *Computers & Industrial Engineering, 80,* 212–221.

Floudas, C. A. (2000). *Deterministic global optimization: Theory, methods and applications*. Boston, MA: Springer.

Gao, K. Z., Suganthan, P. N., Pan, Q. K., Chua, T. J., Chong, C. S., & Cai, T. X. (2016). An improved artificial bee colony algorithm for flexible job-shop scheduling problem with fuzzy processing time. *Expert Systems with Applications, 65,* 52–67.

Gen, M., & Cheng, R. (1997). *Genetic algorithms and engineering design*. New York: Wiley.

Goldberg, D. E. (1989). *Genetic algorithms in search, optimization, and machine learning*. Boston: Addison-Wesley Publishing Company, Inc.

Hanagandi, V., & Nikolaou, M. (1998). A hybrid approach to global optimization using a clustering algorithm in a genetic search framework. *Computers & Chemical Engineering, 22* (12), 1913–1925.

Harrington, J. (1973). *Computer integrated manufacturing*. New York: Industrial Press.

He, N., Zhang, D. Z., & Li, Q. (2014). Agent-based hierarchical production planning and scheduling in make-to-order manufacturing system. *International Journal of Production Economics, 149,* 117–130.

He, Y., & Hui, C. W. (2010). A binary coding genetic algorithm for multi-purpose process scheduling: A case study. *Chemical Engineering Science, 65*(16), 4816–4828.

Hfaiedh, W., Sadfi, C., Kacem, I., & Hadj-Alouane, A. (2015). A branch-and-bound method for the single-machine scheduling problem under a non-availability constraint for maximum delivery time minimization. *Applied Mathematics and Computation, 252,* 496–502.

Holland, J. H. (1975). *Adaptation in natural and artificial systems*. Ann Arbor: University of Michigan Press.

Huang, B., Gao, C., & Chen, L. (2011). Partner selection in a virtual enterprise under uncertain information about candidates. *Expert Systems with Applications, 38*(9), 11305–11310.

Huang, B., Gou, H., Liu, W., Li, Y., & Xie, M. (2002). A framework for virtual enterprise control with the holonic manufacturing paradigm. *Computers in Industry, 49*(3), 299–310.

Huang, M., & Fan, C. (2007). Research on the partner selection of virtual enterprise based on self-adaptive genetic algorithm. In *Third International Conference on Intelligent Information Hiding and Multimedia Signal Processing* (pp. 330–333).

Hyun, C. J., Kim, Y., & Kim, Y. K. (1998). A genetic algorithm for multiple objective sequencing problems in mixed model assembly lines. *Computers & Operations Research, 25*(7–8), 675–690.

Ip, W. H., Huang, M., Yung, K. L., & Wang, D. (2003). Genetic algorithm solution for a risk-based partner selection problem in a virtual enterprise. *Computers & Operations Research, 30*(2), 213–231.

Kahraman, C., Beskese, A., & Ruan, D. (2004). Measuring flexibility of computer integrated manufacturing systems using fuzzy cash flow analysis. *Information Sciences, 168*(1–4), 77–94.

Kundakcı, N., & Kulak, O. (2016). Hybrid genetic algorithms for minimizing makespan in dynamic job shop scheduling problem. *Computers & Industrial Engineering, 96,* 31–51.

Lan, F., Bayraksan, G., & Lansey, K. (2016). Reformulation linearization technique based branch-and-reduce approach applied to regional water supply system planning. *Engineering Optimization, 48*(3), 454–475.

Lee, K., Kim, B. S., & Joo, C. M. (2012). Genetic algorithms for door-assigning and sequencing of trucks at distribution centers for the improvement of operational performance. *Expert Systems with Applications, 39*(17), 12975–12983.

Li, J., & Chan, F. T. S. (2012). The impact of collaborative transportation management on demand disruption of manufacturing supply chains. *International Journal of Production Research, 50* (19), 5635–5650.

Li, J., Huang, Y., & Niu, X. (2016). A branch population genetic algorithm for dual-resource constrained job shop scheduling problem. *Computers & Industrial Engineering, 102,* 113–131.

Liberti, L., & Kucherenko, S. (2005). Comparison of deterministic and stochastic approaches to global optimization. *International Transactions in Operational Research, 12*(3), 263–285.

Lin, G. C. I. (1997). The latest research trends in CIM. In *The Fourth International Conference on Computer Integrated Manufacturing* (pp. 26–33).

Lin, S. Y., & Tsai, H. F. (2016). Micro genetic algorithm with spatial crossover and correction schemes for constrained three-dimensional reader network planning. *Expert Systems with Applications, 44,* 344–353.

Lin, W. C., Yin, Y., Cheng, S. R., Cheng, T. C. E., Wu, C. H., & Wu, C. C. (2016). Particle swarm optimization and opposite-based particle swarm optimization for two-agent multi-facility customer order scheduling with ready times. *Applied Soft Computing*. https://doi.org/10.1016/j.asoc.2016.09.038.

Luo, J., Wu, Y., & Mendes, A. B. (2016). Modelling of integrated vehicle scheduling and container storage problems in unloading process at an automated container terminal. *Computers & Industrial Engineering, 94,* 32–44.

Mahmoodabadi, M. J., Safaie, A. A., Bagheri, A., & Nariman-zadeh, N. (2013). A novel combination of Particle Swarm Optimization and Genetic Algorithm for Pareto optimal design of a five-degree of freedom vehicle vibration model. *Applied Soft Computing, 13*(5), 2577–2591.

Maity, S., Roy, A., & Maiti, M. (2015). A modified genetic algorithm for solving uncertain constrained solid travelling salesman problems. *Computers & Industrial Engineering, 83,* 273–296.

Majumder, A., & Laha, D. (2016). A new cuckoo search algorithm for 2-machine robotic cell scheduling problem with sequence-dependent setup times. *Swarm and Evolutionary Computation, 28,* 131–143.

Marian, R.M., Luong, L. & Dao, S.D. (2012). Hybrid genetic algorithm optimisation of distribution networks—A comparative study, in SI Ao, O Castillo & X Huang (eds), *Intelligent Control and Innovative Computing*, Springer US, Boston, MA, pp. 109-122.

Michalewicz, Z. (1996). *Genetic algorithms + Data structures = Evolution programs*. Berlin, Heidelberg: Springer.

Miller, F. P., Vandome, A. F., & McBrewster, J. (2010). *Computer-integrated manufacturing*. Mauritius: VDM Publishing House.

Moles, C. G., Mendes, P., & Banga, J. R. (2003). Parameter estimation in biochemical pathways: A comparison of global optimization methods. *Genome Research, 13*(11), 2467–2474.

Mun, J., Shin, M., Lee, K., & Jung, M. (2009). Manufacturing enterprise collaboration based on a goal-oriented fuzzy trust evaluation model in a virtual enterprise. *Computers & Industrial Engineering, 56*(3), 888–901.

Nagalingam, S. V. (1999). *An innovative decision support system for CIM justification and optimisation*. Ph.D. thesis, School of Engineering, University of South Australia.

Nagalingam, S. V., & Lin, G. C. I. (1999). Latest developments in CIM. *Robotics and Computer-Integrated Manufacturing, 15*(6), 423–430.

Nagalingam, S. V., & Lin, G. C. I. (2000). A distributed group decision support systems for virtual computer integrated manufacturing. In *The 6th International Conference on Automation Technology* (pp. 377–382).

Nagalingam, S. V., Lin, G. C. I., & Wang, D. (2007). Resource scheduling for a virtual CIM system. In L. Wang & W. Shen (Eds.), *Process planning and scheduling for distributed manufacturing* (pp. 269–294). London: Springer.

Nagalingam, S. V., Lin, G. C. I., Zhou, J., & Wang, D. (2003). Virtual computer integrated manufacturing and its future applications. In *Proceedings of the 17th International Conference on Production Research.*

Ng, C. K., & Li, D. (2014). Test problem generator for unconstrained global optimization. *Computers & Operations Research, 51,* 338–349.

Niu, S. H., Ong, S. K., & Nee, A. Y. C. (2012). An enhanced ant colony optimiser for multi-attribute partner selection in virtual enterprises. *International Journal of Production Research, 50*(8), 2286–2303.

Ozener, O. O. (2008). *Collaboration in transportation*. Ph.D. thesis, Georgia Institute of Technology, Atlanta.

Qing-dao-er-ji, R., & Wang, Y. (2012). A new hybrid genetic algorithm for job shop scheduling problem. *Computers & Operations Research, 39*(10), 2291–2299.

Qu, H., Xing, K., & Alexander, T. (2013). An improved genetic algorithm with co-evolutionary strategy for global path planning of multiple mobile robots. *Neurocomputing, 120,* 509–517.

Salehi, M., & Moghaddam, T. R. (2009). Application of genetic algorithm to computer-aided process planning in preliminary and detailed planning. *Engineering Applications of Artificial Intelligence, 22*(8), 1179–1187.

Sawik, T. (2007). A lexicographic approach to bi-objective scheduling of single-period orders in make-to-order manufacturing. *European Journal of Operational Research, 180*(3), 1060–1075.

Shahlaei, M., Sobhani, A. M., Saghaie, L., & Fassihi, A. (2012). Application of an expert system based on Genetic Algorithm–Adaptive Neuro-Fuzzy Inference System (GA–ANFIS) in QSAR of cathepsin K inhibitors. *Expert Systems with Applications, 39*(6), 6182–6191.

Shahvari, O., & Logendran, R. (2017). An enhanced tabu search algorithm to minimize a bi-criteria objective in batching and scheduling problems on unrelated-parallel machines with desired lower bounds on batch sizes. *Computers & Operations Research, 77,* 154–176.

Shokouhifar, M., & Jalali, A. (2015a). A new evolutionary based application specific routing protocol for clustered wireless sensor networks. *International Journal of Electronics and Communications (AEÜ), 69,* 432–441.

Shokouhifar, M., & Jalali, A. (2015b). An evolutionary-based methodology for symbolic simplification of analog circuits using genetic algorithm and simulated annealing. *Expert Systems with Applications, 42*(3), 1189–1201.

Simona, D., & Raluca, P. (2011). Intelligent modeling method based on genetic algorithm for partner selection in virtual organizations. *Business and Economic Horizons, 5*(2), 23–34.

Stern, H., Chassidim, Y., & Zofi, M. (2006). Multiagent visual area coverage using a new genetic algorithm selection scheme. *European Journal of Operational Research, 175*(3), 1890–1907.

Su, W., Huang, S. X., Fan, Y. S., & Mak, K. L. (2015). Integrated partner selection and production–distribution planning for manufacturing chains. *Computers & Industrial Engineering, 84,* 32–42.

Suresh, S., Huang, H., & Kim, H. J. (2014). Hybrid real-coded genetic algorithm for data partitioning in multi-round load distribution and scheduling in heterogeneous systems. *Applied Soft Computing, 24,* 500–510.

Tang, P. H., & Tseng, M. H. (2013). Adaptive directed mutation for real-coded genetic algorithms. *Applied Soft Computing, 13*(1), 600–614.

Tao, F., Zhang, L., Zhang, Z. H., & Nee, A. Y. C. (2010). A quantum multi-agent evolutionary algorithm for selection of partners in a virtual enterprise. *CIRP Annals - Manufacturing Technology, 59*(1), 485–488.

Wan, Y., Wang, M., Ye, Z., & Lai, X. (2016). A feature selection method based on modified binary coded ant colony optimization algorithm. *Applied Soft Computing, 49,* 248–258.

Wang, D. (2007). *The development of an agent-based architecture for virtual CIM*. Ph.D. thesis, University of South Australia, Adelaide.

Wang, D., Nagalingam, S. V., & Lin, G. C. I. (2003a). Development of a virtual CIM system using agent-based approach. In *Proceedings of the 7th International Conference on Mechatronics Technology* (pp. 445–450).

Wang, D., Nagalingam, S. V., & Lin, G. C. I. (2003b). Development of an optimised virtual CIM system. In *The 17th International Conference on Production Research* (pp. 1–5).

Wang, D., Nagalingam, S. V., & Lin, G. C. I. (2004). Development of a parallel processing multi-agent architecture for a virtual CIM system. *International Journal of Production Research, 42*(17), 3765–3785.

Wang, D., Nagalingam, S. V., & Lin, G. C. I. (2007). Development of an agent-based virtual CIM architecture for small to medium manufacturers. *Robotics and Computer-Integrated Manufacturing, 23*(1), 1–16.

Wang, L., & Zheng, D. Z. (2002). A modified genetic algorithm for job shop scheduling. *The International Journal of Advanced Manufacturing Technology, 20*(1), 72–76.

Wang, N. F., Zhang, X. M., & Yang, Y. W. (2013a). A hybrid genetic algorithm for constrained multi-objective optimization under uncertainty and target matching problems. *Applied Soft Computing, 13*(8), 3636–3645.

Wang, Y., Huang, J., Dong, W. S., Yan, J. C., Tian, C. H., Li, M., et al. (2013b). Two-stage based ensemble optimization framework for large-scale global optimization. *European Journal of Operational Research, 228*(2), 308–320.

Wang, Y., Yin, H., & Wang, J. (2009). Genetic algorithm with new encoding scheme for job shop scheduling. *The International Journal of Advanced Manufacturing Technology, 44*(9–10), 977–984.

Wozabal, D. (2012). Value-at-risk optimization using the difference of convex algorithm. *OR Spectrum, 34*(4), 861–883.

Wu, N., & Su, P. (2005). Selection of partners in virtual enterprise paradigm. *Robotics and Computer-Integrated Manufacturing, 21*(2), 119–131.

Wu, X., Chu, C. H., Wang, Y., & Yan, W. (2007). A genetic algorithm for cellular manufacturing design and layout. *European Journal of Operational Research, 181*(1), 156–167.

Xia, H., Li, X., & Gao, L. (2016). A hybrid genetic algorithm with variable neighborhood search for dynamic integrated process planning and scheduling. *Computers & Industrial Engineering, 102,* 99–112.

Yang, C. O., Guan, T. Y., & Lin, J. S. (2000). Developing a computer shop floor control model for a CIM system—using object modeling technique. *Computers in Industry, 41*(3), 213–238.

Ye, F. (2010). An extended TOPSIS method with interval-valued intuitionistic fuzzy numbers for virtual enterprise partner selection. *Expert Systems with Applications, 37*(10), 7050–7055.

Ye, F., & Li, Y. N. (2009). Group multi-attribute decision model to partner selection in the formation of virtual enterprise under incomplete information. *Expert Systems with Applications, 36*(5), 9350–9357.

Yolmeh, A., & Salehi, N. (2015). An outer approximation method for an integration of supply chain network designing and assembly line balancing under uncertainty. *Computers & Industrial Engineering, 83,* 297–306.

Yu, C., Xu, X., & Lu, Y. (2015). Computer-integrated manufacturing, cyber-physical systems and cloud manufacturing—Concepts and relationships. *Manufacturing Letters, 6,* 5–9.

Yun, Y., Chung, H., & Moon, C. (2013). Hybrid genetic algorithm approach for precedence-constrained sequencing problem. *Computers & Industrial Engineering, 65*(1), 137–147.

Yurdakul, M. (2004). Selection of computer-integrated manufacturing technologies using a combined analytic hierarchy process and goal programming model. *Robotics and Computer-Integrated Manufacturing, 20*(4), 329–340.

Yusuf, İ. T. (2012). An experimental design approach using TOPSIS method for the selection of computer-integrated manufacturing technologies. *Robotics and Computer-Integrated Manufacturing, 28*(2), 245–256.

Zeng, Z. B., Li, Y., & Zhu, W. (2006). Partner selection with a due date constraint in virtual enterprises. *Applied Mathematics and Computation, 175*(2), 1353–1365.

Zhang, Y., Tao, F., Laili, Y., Hou, B., Lv, L., & Zhang, L. (2012). Green partner selection in virtual enterprise based on Pareto genetic algorithms. *The International Journal of Advanced Manufacturing Technology*, 1–17.

Zhang, Y., Tao, F., Laili, Y., Hou, B., Lv, L., & Zhang, L. (2013). Green partner selection in virtual enterprise based on Pareto genetic algorithms. *The International Journal of Advanced Manufacturing Technology, 67*(9), 2109–2125.

Zhao, J., & Wang, L. (2011). Center based genetic algorithm and its application to the stiffness equivalence of the aircraft wing. *Expert Systems with Applications, 38*(5), 6254–6261.

Zhao, Q., Zhang, X., & Xiao, R. (2008). Particle swarm optimization algorithm for partner selection in virtual enterprise. *Progress in Natural Science, 18*(11), 1445–1452.

Zhong, T. X., & Chen, J. C. (2002). A hybrid-coded genetic algorithm based optimisation of non-productive paths in CNC machining. *The International Journal of Advanced Manufacturing Technology, 20*(3), 163–168.

Zhong, Y., Jian, L., & Zijun, W. (2009). An integrated optimisation algorithm of GA and ACA-based approaches for modeling virtual enterprise partner selection. *The DATA BASE for Advances in Information Systems, 40*(2), 37–56.

Zhou, N., Xing, K., & Nagalingam, S. V. (2010a). An agent-based cross-enterprise resource planning for small and medium enterprises. *IAENG International Journal of Computer Science, 37*(3), 1–7.

Zhou, N., Xing, K., Nagalingam, S. V., & Lin, G. C. I. (2010b). Development of an agent based VCIM resource scheduling process for small and medium enterprises. In *Proceedings of the International MultiConference of Engineers and Computer Scientists* (pp. 39–44).

Zhou, W., Zheng, J., Yan, J., & Wang, J. (2011). A novel hybrid algorithm for assembly sequence planning combining bacterial chemotaxis with genetic algorithm. *The International Journal of Advanced Manufacturing Technology, 52*(5–8), 715–724.

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