SEMARAK ILMU PUBLISHING
202103268166(003316878-P)

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage: https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

A Comprehensive Review of Different Approaches used by Manufacturing Industries in Handling Capacity Planning under Demand Uncertainties

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ARTICLE INFO

Article history:
Received 28 February 2024
Received in revised form 30 April 2024
Accepted 30 June 2024
Available online 10 August 2024

Keywords:
Optimization; simulation approaches; applied science system; technology; flexibility

ABSTRACT

In today's dynamic industrial environment, efficient capacity planning is of essential relevance, especially in the face of unpredictable and fluctuating client demands. Failure to address demand uncertainty may lead to undesirable effects, such as overproduction or underproduction. This study carefully analyses variety of capacity planning approaches employed by the industry. Additionally, the research extended to explore several simulation approaches employed as powerful tool in tackling capacity planning issues, delivering adaptable solutions that respond to the particular demands of both major organizations and small to medium-sized firms. This analysis underlines the vital role of simulation in increasing operational performance, optimizing resource allocation, and reacting to changing production needs, eventually leading to greater competitiveness and efficiency within the manufacturing industry.

1. Introduction

Amidst the dynamic and always evolving industrial environment, it is vital to spend resources strategically in order to successfully answer the unanticipated market demands. Managing supply chain and production volatility is one of the main challenges of modern production network. Failure to appropriately address volatility in manufacturing may represent a serious danger to responsible and resource-efficient production. This may result in two extreme scenarios: overproduction or underproduction, both of which have adverse consequences on operations [45].

According to Chen *et al.*, [12], most businesses engage three stages of capacity planning, namely long-term, medium-term, and short-term capacity planning, in order to sustain a given demand over a planning horizon. According to Olhager *et al.*, [48], capacity is frequently handled at a collective level, concentrating on significant labour hubs and projecting the demands of product families. The normal timeline for long-term capacity planning is from 1 to 5 years. This planning focuses on capabilities that take substantial time to adjust, such as obtaining extra capacity or lowering current capacity levels. The basic rationale for this strategy is that capacity gains occur in major, identifiable

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https://doi.org/10.37934/araset.50.1.88106

increments rather than in tiny, gradual adjustments. From a usual operational approach, capacity may only be adjusted in discrete increments with a large amount of prior warning as shown in Figure 1.

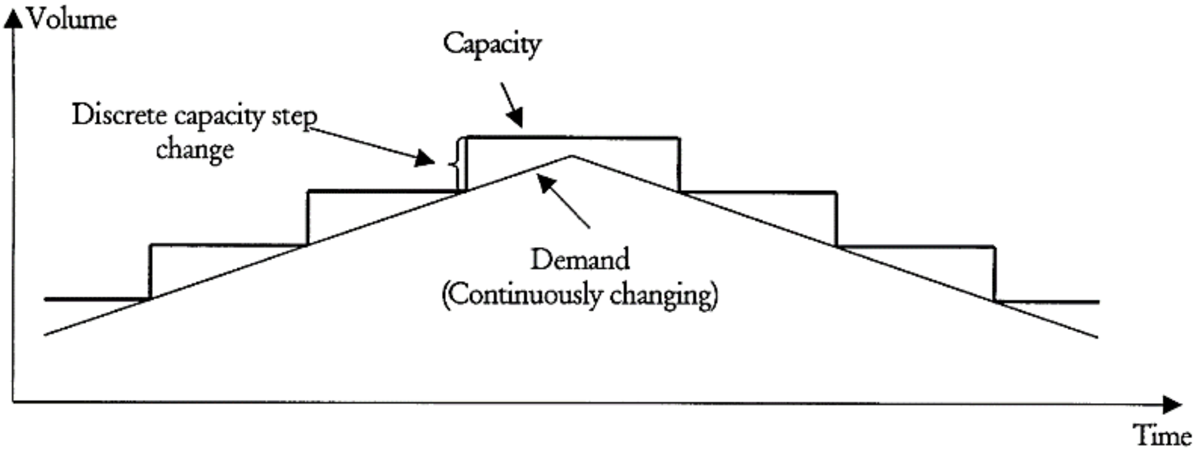


Fig. 1. Capacity step wise change over continuous demand change [48]

Another notable issue in capacity planning is capacity expansion, Chou *et al.*, [16] separated it into two key aspect which are the scheduling and the size model of each expansion. Scale of increased capacity is considered in sizing methodology while timing method suggests the best period for future development. The study found that the temporal capacity expansion model outperformed the size strategy. In their research, Giovanni and Massabò [20] studied the most favourable timing and quantity of investment in the context of unforeseen demand and the flexibility to adjust output volume. Two distinct models of volume flexibility are applied in the studies: downside flexibility (the ability to downscale production below installed capacity) and upside flexibility (the ability to produce above installed capacity). It was discovered that the quantity of investment was lesser and the capacity utilization rate was larger and being maintained in upside flexibility model.

This paper's objective is to examine how do most manufacturing sector employ numerous approaches and methodologies into determining the most suited capacity and investment into their planning, in order to support unexpected and uncertain client demands. The research is further progressed into many simulation ways applied in operation environment in regulating diverse capacity and demands scenarios. To date, there have been several research including IoT (Internet of Thing) and sustainability concept into the capacity planning debate due to sustainable advancement and the preservation of the environment are receiving considerable emphasis within the industrial sector [40]; nevertheless, it appears to be relatively limited studies to incorporate emotional engineering technique into the framework of capacity planning decision making process. In the context of production and capacity planning, it could entail examining the emotions and experiences of workers, customers and other stakeholders in decision-making processes.

2. Demand Uncertainty and Capacity Planning

Chiang *et al.*, [11] defined demand uncertainty as the actual demand varies from projected demand due to uncontrolled or expected source. There are different methods to interpret demands, for example, Angkiriwang *et al.*, [2] evaluated demand uncertainty in:

i. Probabilistic nature of demand amount, type, time and location
ii. Form of defects in the form of demand forecast
iii. Uncertainty on production mix in client orders
iv. Changes in customer orders
v. Competitors action towards marketing promotion.

Whereas for Yazici *et al*., [59], they noted that demand uncertainty should have coverage of demand, return, product design, recycling and distribution uncertainties. Furthermore, Polotski *et al*., [49] distinguish demands into variability and uncertainty where value is known for demand variability, however value is not precisely known for the case of demand uncertainty. When looking at investment standpoint, Ogawa and Suzuki [46] in their study for Japan industrial sectors, have shown in most situations there was a substantially negative connection between uncertainty and fixed investment. In addition, more sensitive impact occurred towards material industry group than for machinery industry group. Same for Italian manufacturing films, Bontempi *et al*., [5] in their study have explained the adverse association between demand uncertainty and investment decision. Further inquiry revealed that the effect of uncertainty regarding investment plan would become reduce for companies that employed more flexible workforce input.

In the context of capacity planning, there are three forms of demand uncertainty to be considered: scenarios, random variables and stochastic processes. It was also depicted as imprecise distribution formed from numerous initial estimations [14]. Besides, Lin *et al*., [39] used three demand states, H; M; L, to indicate demand uncertainty or stochastic market condition: H (above-forecast state); M (consistent with forecast average); L (below-forecast average). High degree of uncertainty could lead to unplanned alterations to manufacturing equipment in production capacity planning. The product demand is anticipated to follow a continuous probability distribution via approximated discrete scenarios was mentioned in the study of Dering and Swartz [21] for chemical processing industry, where the demands scenarios of low, medium and high were exhibited in normal distribution. Similarly, demand uncertainty is simulated to follow a discrete distribution with known probability, as indicated by Gozali *et al*., [26] and Felfel *et al*., [23].

Cardoso *et al*., [8] in their European supply chain case study evaluated three demand scenarios:

i. optimistic scenario where assumption of 10% growth in demand in the following period with a chance of 0.25
ii. realistic scenario where assumption of 3% increase in demands with a probability of 0.5
iii. sad scenario where assumption of 5% decrease with a probability of 0.25.

Chuang and Chiang [17] defined demand uncertainty as sigma demand in their study to examine finished-goods inventory in the U.S. automobile industry using economic order quantity (EOQ) model.

Studies have been conducted to manage uncertainty in manufacturing production and equipment planning, such as Burggräf *et al*., [7] developed a holistic model to identify and evaluate uncertainty to support in decision-making of agile equipment planning process, which include fuzzy logic and Design for Changeability as key methods. Kuo and Chien [33] build sets of demand scenarios for minimax regret capacity expansion model applying both additive and multiplicative martingale models of forecast evolution (MMFE) for the semiconductor industry. Another new and robust strategy named Elastic p-Robustness approach was introduced. This approach was able to estimate probability distribution of random components associated with supply and demand changes when historical data is constrained or did not exist. Their investigation indicated that the unique method outperformed the existing robustness algorithms which include minimax cost, minimax regret and p-Robustness in terms of both supply chain cost and relative regret.

Zhang [60] addressed capacity planning in both ways of capacity expansion and reduction. Capacity planning may be based on different models; some are deterministic, some are based on unknown demands, others are based on stochastic capacity and still others use fuzzy judgment. Among these, stochastic model is generally viewed more realistic because stochastic component happens in real in both market and production system (including some uncertain attributions in production capacity such as random failure in activity centre). Antomarchi *et al*., [3] reviewed the definition of capacity planning from different literatures and one of them include capacity planning as a decision-making process which determine the order and timing of acquisition or the sale of resources. Capacity utilization is continuously related with the issue of capacity planning. While since long back, Ragan Jr [52] revealed in the research that projection of capacity utilization is the consequence from the forecast of output divided by the forecast of capacity. Furthermore, according to Corrado and Mattey [18], capacity utilization is a ratio of the present level of production to a sustainable maximum level of output. Rimo and Ong [55] offered the usual definition of capacity utilization as a ratio of actual production to the potential output of a machinery; where potential output refers to the capacity of the machinery. This may be measured either in engineering viewpoint or economic perspective.

Singh *et al.,* [56] noted that capacity utilization is a relative indicator which informs the rate of the utilized capacity of the plant while it is determined using time series technique, survey method, economic approach and engineering approach in global industrial sectors. Based on Okunade and Oluwaseun [47], capacity utilization is measured in 100% efficiency level in theory, however in real manufacturing environment, due to some setbacks in the production process which coupled with wastages and breakdown, capacity utilization may not exceed 90% maximum level as practical. Each manufacturing organization will develop their best degree of utilization based on the concept of cost optimization.

3. Capacity Planning Strategies in Manufacturing Industry

There have been numbers of studies performed out in examining production capacities over a projected horizon in order to aid manufacturing films in their decision making on capacity expansion or new manufacturing system design. Ceryan and Koren [10] had their analysis focused on the optimal capacity investment options for a firm producing diverse items over a planning horizon. The study aided the firm in determining how much capacity to construct for their new system and whether to invest in dedicated or flexible systems or mix of both. In addition, the study broadened the analysis of optimal capacity investments to numerous selling periods, nonstationary demand processes based on product life cycles and discrete increment of capacity purchases. The applied analysis entails constructing a mathematical model evolve around the k factor (capacity investment decision) and d factor (product requirements throughout the planning horizon) for the capacity investment problem. Numerical calculations were carried out to determine the optimal capacity investment choice. Finally, the data revealed that a portfolio strategy consisting of both dedicated and flexible capabilities were able to provide bigger returns compared to single scale investment (dedicated or flexible system).

Chen *et al.,* [13] completed a study to provide response towards customers' stochastic demands in food processing industry. The study was separated into three approaches: First, a case study designed to evaluate the food processing and its special production limits. Data gathered were collated and a mathematical model was given for production schedule planning. Second, the model was expanded to accommodate unforeseen demand and it was applied to develop three-week production plan. The probabilistic constraints of uncertain customer demand were transferred to the equivalent deterministic constraints using chance constrained programming (CCP). The limits were product diversity, changeover in production line and allocation of labour in each product. Third, historical data was employed to study the effect of three forecasting methodologies (moving average method, expected mean method and CCP method) on out-of-stock and inventory cost. The study was able to accomplish 95% customer service level for the three-week production plan applying CCP to overcome the random demand constraint. Also, CCP methodology (at defined customer service level) demonstrated higher performance on the sum of out-of-stock cost and inventory expenditures than moving average method and the expected mean method.

Another study in food producers investigated the capacity investment and the benefit of flexibility in the context of product blending constraints [31]. This study assessed the stochastic programming under demand uncertainty of the food production system employing a newsvendor networks kernel. In their built model, K represent the optimal capacity acquisition vector while product demand was represented by vector D. Then, the Lagrangian problem is formulated and optimality criteria were devised. The numerical calculations indicated that a tiny amount of blending of intermediate was able to boost flexibility substantially. One of the main take-away from the study was on its model constraint which would seem to be extremely stylized in its application. However, it was agreed that the simplification allowed them to acquire some broad insights into the issue which offer guidance in capacity investment possibilities.

Real option analysis (ROA) was widely disputed in investment theory. One of the studies that accept this was from Giovanni and Massabò [20] who completed their study on effect of volume flexibility towards capacity investment in monopolistic firm. In this study, the film was facing with 2 dilemmas in their decision making; one is choosing a small capacity that allowed the firm to contemplate the possibility of suspending production in the future but made more costly adjustment of production volume at higher demand’s level; second was investing in large capacity that implied lower cost of production adjustment when demand boomed; however, the firm was not able to suspend the production if the market crashed. This article classified volume flexibility into two: downside volume flexibility (produced quantity below installed capacity) and upside volume flexibility (created quantity exceeding capacity). The study demonstrated that upside volume flexibility gave combined effect in term of investment size reduction and investment threshold. Besides, utilization rates were recognized bigger as the upside flexibility increased.

Another real option analysis (ROA) was published in study done by Seifert *et al.,* [54] for multiproduct continuous plant for three separate recombinant proteins. ROA was applied to examine the influence of uncertain market development on four separate modules with various growth stages. The framework had two stages: Stage 1 was to identify workable modular configurations and acceptable expansion techniques; step 2 was to assess its economic performance in an unpredictable market. Four distinct modules were put up which necessitated various sizes and bare equipment cost for 6 comparable equipment. Setup 1 (3.0 m^3 fermenter size) is the smallest modules that allow smaller plant growth stages. Setup 2 (5.0 m^3 fermenter size) and Setup 3 (8.0 m^3) employ larger fermenter modules with higher expansion stages. Setup 4 is a fermenter module with a medium size, to be employed in analysing the impact of module selection of the downstream section. Decision making focuses on the economic performances of the different setup options based on several market situations. The market scenarios created in the study were:

i. base case scenario (fixed product mix and a demand growth over 10 years from 5 tones/annum to 10 tones/annum)
ii. variations of demand uncertainty
iii. changes on product pricing
iv. evolution of demand development.

The study suggested that module selection played a vital role for the creation of flexibility at reasonable cost. For example, amid more volatility's situation (scenario 2), smaller module size enhanced managerial flexibility and generated better expanded net present value (ENPV).

Heitmann *et al.,* [29] proposed a modular design that enables possibilities of a progressive capacity increase for future plant concept; which allow an efficient and adaptable manufacture of new products. In this study, a framework to evaluate the production capacity of a modular multi-product plant for capacity expansion, considering economic performance and investment risk was addressed. A decision tree analysis (DTA) was performed to integrate production planning using a capacitated lot size technique, which was established to examine the economic performance of plants with changing capacities in an uncertain market. Additionally, the study discussed the NPV (Net Present Value) distribution and investment risk analysis for modular production lines with different capacities. The output of the framework was applied for a case study of a set of three separate items. As a result, the study suggested that a smaller scale production may minimize the investment risk by minimizing the fixed and setup expenses and it also provide opportunity to maintain profitability by an expansion strategy at reduced investment risk.

Antomarchi *et al*., [3] addressed a deterministic problem of capacity planning for additive manufacturing and proposed a way for organizations to evaluate the optimal design approach under uncertainties of demands, resource development, cost and technology evolution. The approach supported judgment towards time when machine can be obtained, period when alternatives (other technologies on the machine) can be purchased and period when evolution (productivity and availability of the machines) can be purchased. In the study, a unique model was developed which may be applied to integrate both market and machine uncertainty and the attitude of decision-maker on risk management. As the first strategy, the authors constructed a mixed integer program by combining varied expenditures to obtain the goal function of net profit optimization. There were four demand scenarios utilized to the optimization model. Scenario 1 with quick increase of demand and stability in machine evolution; Scenario 2 with gradual increase of demand and stable in machine evolution; Scenario 3 with average increase of demand and stable in machine evolution and Scenario 4 with average increase of demand but quick evolution (productivity and availability) on machines. The results indicated the effect of demand uncertainties and machine uncertainty on the net profit of the company.

As a novel engineering response to volatile global markets challenge especially on forecasting future product demands, reconfigurable manufacturing systems (RMSs) were invented in the last decade of twentieth century [36]. Figure 2 depicted the manufacturing invention evolution in Michigan where RMS emerge as its latest inventions which was discussed by Koren *et al.,* [34].

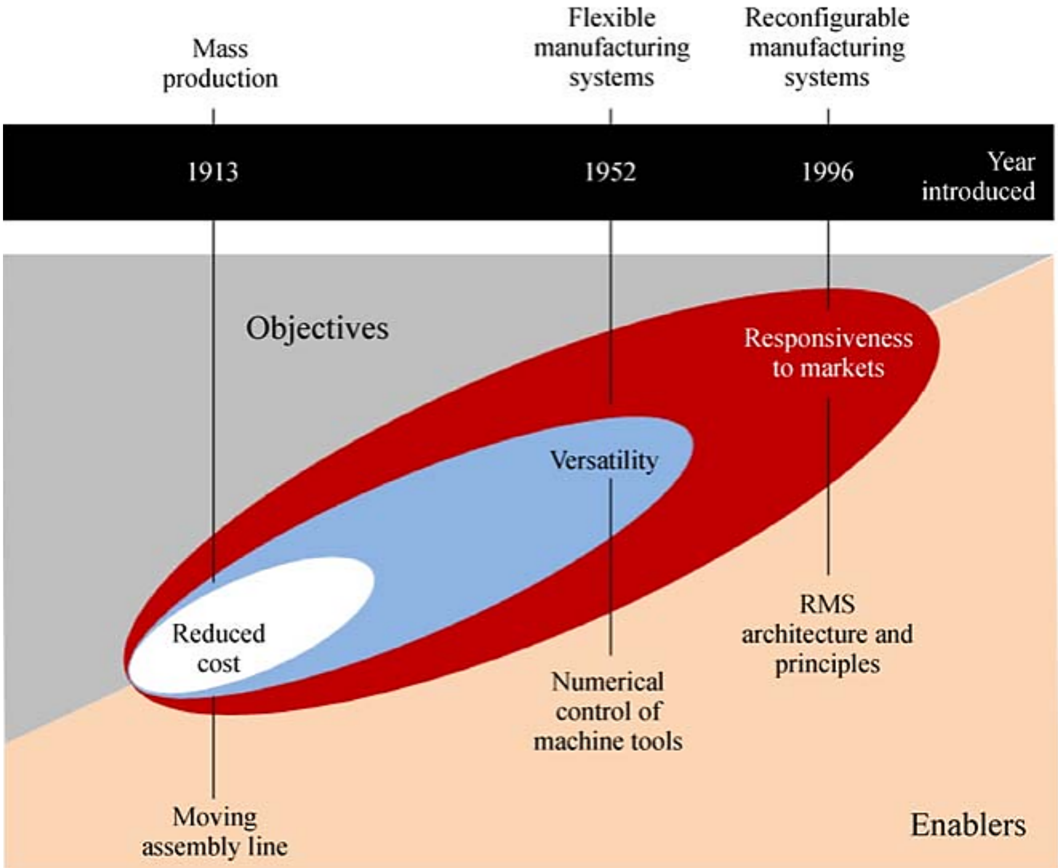


Fig. 2. Manufacturing inventions initiated in Michigan [34]

Niroomand *et al*., [43] in their study has evaluated among dedicated manufacturing systems (DMS), flexible manufacturing system (FMS) and reconfigurable manufacturing system (RMS) to best decide on its capacity investments during the ramp up phase. Analysis of the capacity selection was done based on three basic patterns which are classic, Growth-plateau and Cycle–recycle. In the recommended model, capacity investment may be done on each of DMS, FMS, and RMS or a mix of those systems. The purpose was to evaluate the effect of different system scalability characteristics on capacity selection. Findings from the study revealed that RMS offer greater responsiveness in all demand life cycles, it can follow aggregate demand with least spare capacity. For certain cycle-recycle life cycle demands, a mix of RMS and FMS was adopted. In traditional life cycle need with quick setup time, RMS was again advised to be more suitable. However, with the longer reconfiguration time, it was desirable to have combination of DMS and FMS. Finally, a mix of all RMS, FMS and DMS best suit in growth-plateau life cycle demands as the reconfiguration time increase.

Extensive literature analysis of Reconfigurable Manufacturing Systems (RMSs) from 1999 to 2017 was done by Bortolini *et al.,* [6]. In their review, RMS was compared with other contemporary manufacturing systems, namely Dedicated Manufacturing Systems (DMSs), Flexible Manufacturing Systems (FMSs) and Cellular Manufacturing Systems (CMSs) as presented in Table 1. The comparison indicated that RMS outperformed other production techniques in the context of flexibility, machine structure, productivity and variety.

Table 1
Comparison among the features of the existing manufacturing systems [6]

Features	DMS	FMS	CMS	RMS
Cost per part	Low	Reasonable	Medium	Medium
Demand	Stable	Variable	Stable	Variable
Flexibility	No	General	General	Customized
Machine structure	Fixed	Fixed	Fixed	Changeable
Product family formation	No	No	Yes	Yes
Productivity	Very high	Low	High	High
System structure	Fixed	Changeable	Fixed	Changeable
Variety	No	Wide	Wide	High

Furthermore, six important aspects of RMS make it a dynamic system that can follow market evolution especially in term of capacity and functionality. The core system enables modularity, integrability, diagnosability, convertibility, customization and scalability. Among all these elements, scalability has closest relation with the production capacity planning as it facilitates change on system production capacity to match product demands [24]. Table 2 shows recent research (since year 2017) relating to capacity scalability in RMS manufacturing.

Table 2
Recent studies relating to scalability in RMS manufacturing

Articles	Findings
Abdi and Labib [1]	The study contributes to the novelty regards to indication of RMS distinguishing characteristic of scalability for capacity adjustment in a supply chain under the impact of product family life cycle.
Hees *et al.,* [28]	The paper presents a novel production planning method to realize capacity scalability and functionality changes within the planning processes, by optimizing the potential of RMS.
Koren *et al.,* [37]	The study proposes a set of principles for scalability of system design in order to maximize the economic value of the manufacturing system.
Haddou Benderbal *et al.,* [27]	The study considers a multi-objective RMS design approach for selecting a best process plan and the completion time in order to address the problem of machines selections.
Bhargav *et al.,* [4]	The study is to minimize the make span of selected product in RMS, by segregating and scheduling the similar operations of product, in different metaheuristic approaches.
Prasad and Jayswal [50]	The study proposes a modified reconfigurable layout for assembly line and product scheduling on the basis of reconfiguration effort in an automotive industry.
Koren *et al.,* [35]	This study analyses and compare performance of system configuration for high-volume manufacturing, which includes serial lines, parallel system, serial lines in parallel (SLP) and RMS. Performance is evaluated in terms of investment cost and throughput, responsiveness to market change and product quality.
Moghaddam *et al.,* [41]	The study presents two new approaches (integer linear programming (MILP) and integer linear programming (ILP) formulations) to address changes in initial RMS configuration and system's capacity scalability for part family.
Gola *et al.,* [24]	The study aims to identify structure of the new RMS during design stage which allow to maintain expected level of productivity, during the situation when the level of reliability of machine tools decreases and when new machines are added to the system.

Cerqueus and Delorme [9]	The study focusses on evaluating the scalability of RMS at the design stage by using multi-objective purpose for new measurement on all configurations.
Zhang *et al.,* [19]	The study investigates the approach to design and reconfiguration of single-product scalable reconfigurable robotic assembly line (RAL) under fluctuating demands periods.

4. Simulation-Based Approaches for Capacity Planning and Optimization in Manufacturing

In manufacturing industry nowadays, simulation approaches have become increasingly prevalent as powerful tools for resolving a broad range of challenges and assisting decision-making processes. By simulating and modelling industrial processes, researchers and practitioners may examine alternatives to optimize capacity utilization, increase operational efficiency and fulfil fluctuating production demands. Various literatures have offered the equivalent insights on the efficacy of simulation approaches in assisting the industry to obtain outstanding operational performance and increase competitiveness. Figure 3 depicts number of articles on simulation in manufacturing system that have continually climbed in trends from 1970s.

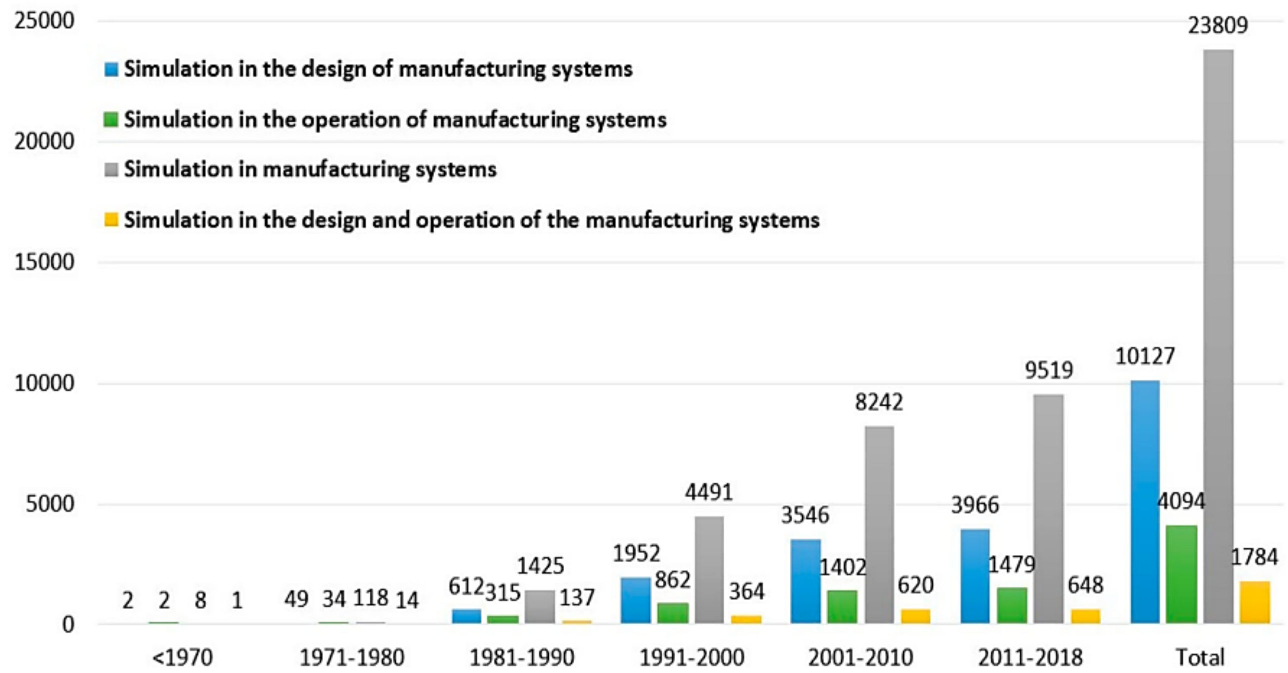


Fig. 3. Number of publications on simulation in manufacturing system based on Scopus database score [42]

To date, various studies have been done, with a specific focus on capacity enhancement within the semiconductor industry. This emphasis is partially connected to the uniqueness of the industry, which is defined by its sensitivity to swings in demand and variations in product mix. For example, Hood *et al*., [30] have proposed a tool set by applying stochastic integer programming technique to solve demand uncertainty for a single demand profile. It improved the decision on the tools to purchase within a budget constraint as well as to lessen the weighted average un-realized demand. Chien *et al*., [15] have solved the tough capacity expansion and migration choice issue by adopting Markov decision process (MDP). The approach facilitates capacity migration, varying lead time on capacity expansion and connectivity between demands and different technologies in semiconductor. During the recent years, Chien *et al*., [14] had gone further on the research to investigate the newgeneration products planning judgments due to the quick rise in semiconductor technology. The study was done to offer a model leveraging uncertain multi-objective decision (UMD) framework to decrease probable loss from capacity surplus or shortage under uncertainties.

Still in semiconductor industry with its growing difficulties, Ziarnetzky and Mönch [61] applied Discrete Event Simulation (DES) in their study on integrated production planning and capacity expansion issue. A cost-based target function was applied in the study, which include lowering the total of inventory, WIP (work in progress) cost and backlog cost; difference of the realized profit and penalty terms and capacity expansion costs. Simulation model contains FE (front end) model which include roughly 200 machines organized in 69 work centres and BE (back end) model which composed of 23 work centres. FE lots comprised of 48 wafers whilst BE lots included 16 wafers. First product's route had 211 process steps in FE and 25 process steps in BE facility; second product had 246 process steps in FE and 31 process steps in BE. Capacity expansion capacity was supplied by activating additional units employing preventive maintenance orders. Five alternative demand scenarios with low and high mean utilization levels were designed for the experiments. Result of the study indicated that SA (simulating annealing) scheme picked the least bottleneck usage in the FE facility and the amount of boosted capacity in the BE facility. Overall, the recommended simulation-optimization approach beat the usual planning formulation.

Other than semiconductor, Kumar and Nottestad [32] applied discrete-event simulation and performed experiments to model and investigate a sequential plastic component manufacturing process. The author examined the use of front-end engineering approaches to better the decision-making processes related to capacity planning, capital equipment selection and the control strategies. Their study tried to develop a semi-automated manufacturing line utilizing conventional technology that may result in cost savings. From the modelling and trials, it allowed the team to determine equipment capabilities, grasp failure circumstances and analyse control methods. With the combined use of Design of Experiment (DOE) and simulation in this study, the variables in a simulation defined machines, conveyors, buffers and labour and can simply be tweaked to assess the effect on manufacturing system performance. While DOE was used to analyse the simulation results and supplied information on the responses from specified variables. Numbers of input and output rules were applied and specified for each of the simulation components, for example mean machine cycle time, buffer capacity, machine Mean Time to Repair (MTTR), lot size, machine changeover time, buffer deadband and etc. were selected in this study for the DOE. As a result, the simulation aided the team in the selection of standard equipment rather than the unique equipment for the intended production line. Furthermore, the standard equipment gave such advantages in term of lower cost and speedier lead time. Whereas the DOE equations for the different responses including throughput analysis, cycle violation analysis and maximum component count analysis assisted the engineers to make fair assumption on equipment performance.

Optimal deployment of capacity investments at the tactical decision-making level was examined by Niroomand *et al*., [44]. In their study, a Mixed Integer Programming (MIP) model was developed to analyse how varied RMS settings have effect on responsiveness and customer service level. At the same time, ramp-up time and capacity availability during the reconfiguration phase are included into the model as a function of added or withdrawn capacity. Subsequently, Discrete Event Simulation model was built to test with demand uncertainty. The simulation result has proved that when developing an RMS, it should be targeted at choosing the configurations that may offer a greater capacity scaling. As one of the studies had proven that when scalability of RMS grew, the manufacturer was able to decrease the lost opportunity cost even when the speed of reconfiguration was only small.

Gómez-Rocha *et al.*, [25] designed two multi-stage stochastic linear programming models to be utilized to build aggregate production plan (APP) for a Mexico's furniture sector. In the constructed model, production periods are treated as the states; whilst production capacity and demands are regarded as random variables which are represented by a continuous probability distribution applying stochastic programming solver. A deterministic model was built with the objective function to lower the total cost of APP; it consisted labour cost, inventory costs, backlogs and production cost. There are two models presented in the study: Model-I coupled the random parameters of production capacity and demands to a normal distribution, and a scenario tree with comparable likelihood of occurrence for each scenario was built. While Model-II displayed the scenario tree with shifting probabilities for each scenario was provided by a discretization of the probability distribution. These two models were evaluated based on the effect of the percentage of service level and features of probability distribution. Between the two models, an optimization gap was calculated. Result from the study indicated that Expected Value (EV) - expectation of all situations, had minor disparity between the two models. Model-II was decided to be more convenient for a speedy decision-making purpose. The study was complemented by undertaking sensitivity analysis to adjust the parameters of the probability distribution or stochastic parameters in order to analyse the implications of the solutions and decision factors. This had benefited the organization in more accurate planning in case those criteria varied in the future.

A dynamic multi-site capacity planning problem was examined by Lin *et al.*, [39] in the thin film transistor liquid crystal display (TFT-LCD) industry who currently applied the deterministic model in their strategic capacity planning operations. The study addressed the capacity expansion decision to meet the projected stochastic demands, by calculating the acquired amount of new auxiliary tools and increased quantity of product group-specific capacity within a set time. A two-stage stochastic programming known as Stochastic dynamic programming (SDP) model with an integrated linear programming (LP) was applied to develop a capacity planning strategy as per newly available demand information, and it was evaluated against current deterministic model. The SDP model analysed numerous capacity growth and budget limits using backward induction approach; however, the LP model provided a choice on capacity allocation plan. Verification of the practicality of the recommended concept was done towards a TFT-LCD manufacturer in Taiwan. The capacity allocation decision was characterized by a created equation which reflected product amounts of product group k at site i in period of t. LP model will produce the option under the demand situation and total purchase amount of new auxiliary tool. Three various problem size (location, product, time) with 10 different cases each were analysed to show and assess the consequences of SDP model versus current paradigm. From the conclusion of the study, it demonstrates that SDP model generated larger overall profits and it was not susceptible to demand uncertainties; this was further verified using Monte Carlo simulation. As conclusion, the SDP model was evaluated to outperform the deterministic strategy now utilized by the organization.

Another simulation methodology done by Renna [53] who devised a decision-making method based on Gale-Shapley model (a Game-Theory algorithm) for reconfiguration of machines in a work shop context. The Gale-Shapley approach intended to find stable matching between two equally groups of things and for each element there was an ordering preference. This design developed a network of over-loaded and under-loaded machines with controlled number of machines' configurations. The simulation model was done based on 3 (Bottleneck's circumstances) x 5 (Tp parameter) x 3 (K- threshold) + 3 (Benchmark) with a total of 48 scenarios produced. Tp refers to periodic review time to analyse the reconfiguration of machines in production system; K-threshold refers to the breadth of zone on average use of the machine. The simulation result demonstrated improvement of all performance metrics (on time delivery, machine throughput and workloads) in all simulated conditions compared to benchmark (without reconfiguration and workload management technique). Eventually, the study was able to support the management option to analyse investment in reconfigurable machines.

In another study by Diaz *et al.,* [22], it proposed a simulation-based multi-objective strategies for the reconfiguration of multi-part lines in reconfigurable manufacturing systems (RMS). The purpose of the study was to improve throughput and minimize total buffer capacity simultaneously in managing fluctuating production volumes. A Simulation-Based Multi-Objective Optimization (SMO) tool called FACTS Analyzer was applied in this study, where a discrete event simulation engine and numerous optimization algorithms were merged and used to simulate the manufacturing line and carry out all the optimization runs. Number of elements such as processing times, times to repair and buffer capacity were introduced as option variables with different possible combinations. The study demonstrated that the recommended SMO approach was able to aid production planning and management of RMS when the organization encounters shifting production volumes. It was also discovered that the recommended SMO approach was not constrained to be utilized to production systems with modular machines, it could also be used to human-based assembly with changeable configuration.

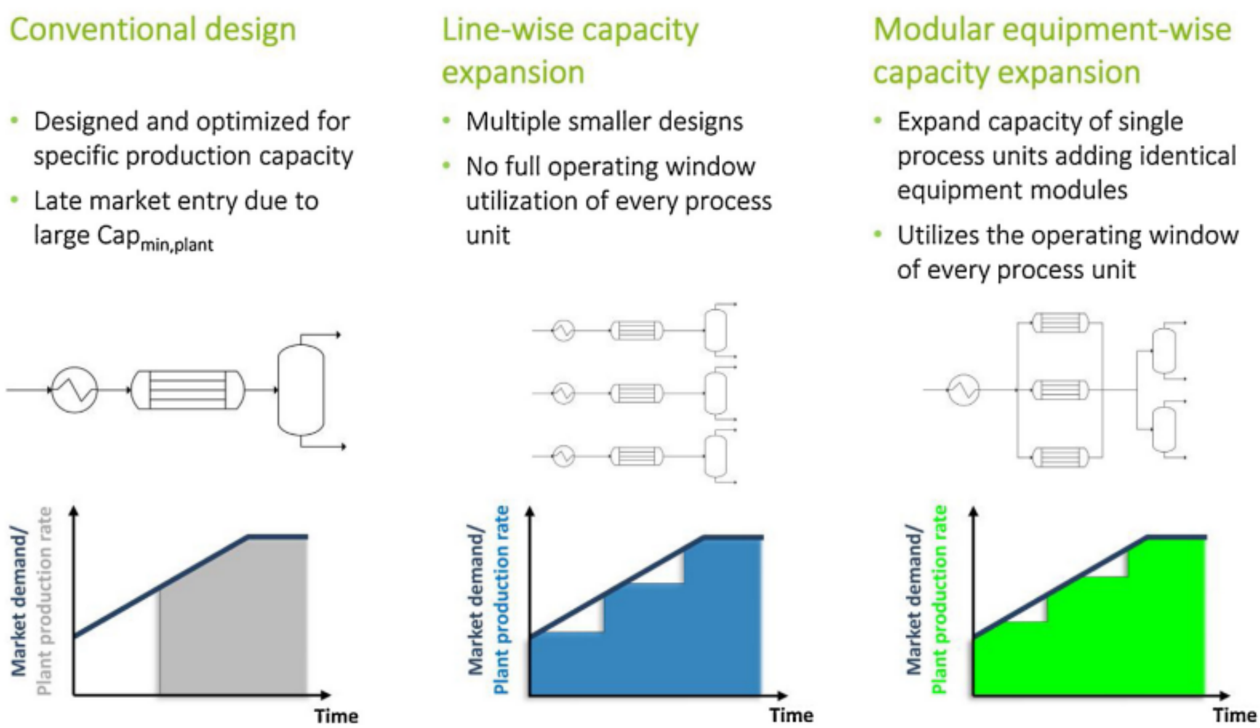
One of the manufacturing difficulties namely a capacity expansion problem (CEP) was addressed in the study done by Lee and Charles [38]. There were 4 proposed models applied to conduct comparison in the study as mentioned in Table 3, such as Basic Model, ULB (Upper Bound and Lower Bound) Model, EV (Expected Value) Model and SP (Stochastic Programming) Model. Each model was explained in such a way that “Basic Model” minimized the maximum capacity regret in terms of all demand scenarios in avoiding worst case; “ULB Model” combined at demand scenarios into the upper bound and lower bound and further simplified into 2 extreme scenarios; “EV Model” made assumption that all demands scenarios was likely to occur only when there was no knowledge indicating unequal probabilities. Lastly, “SP Model” coupled stochastic programming (SP) with predicted recourse problem to alter the variable input level based on the demand forecasting. It analysed the capability regret for minimizing the predicted recourse function. The study demonstrated that proposed SP Model gave more robust solution in managing capacity surplus and capacity deficiency.

Table 3
The comparison of four proposed models on capacity expansion problem [38]

Models	Basic Model	ULB Model	EV Model	SP Model
Strengths	Consider all scenarios	Easy understanding	Easy understanding	Not sensitive to the worst case
Drawback	Sensitive to the worst case	Creates extreme worst case	Dilutes the worst case	Computational burden if there are too many scenarios
Feasibility	Yes	Non necessary	Non necessary	Yes
Managerial Implication	Avoid the worst case	Conservative solution, avoid the ideally worst case	Over optimistic solution, only consider expected value	Robust solution

Applicable Environment/ Condition	Too many scenarios, risk aversion	Risks extreme aversion	Only a few scenarios with small variance	Too many scenarios, capital intensive, competitive market

In addition, Radatz *et al.*, [51] designed framework for identifying best strategy for equipment-wise capacity development in chemical manufacturing plant. The study aimed to build a modular equipment-wise capacity expansion techniques in order to uncover the ideal trade-off solutions between initial investment risk and adaptability to a market requirement. A modular equipment-wise capacity expansion method picks the ideal time and the best size of expansion step utilized to the dehydrogenation of isopropyl alcohol to acetone. Indicators included $TC_{initial}$ which indicate initial investment risk and NPV (net present value) demonstrate profit and adaptability to the market demand development. Difference between conventional design, line-wise capacity expansion and modular equipment-wise capacity extension was displayed in Figure 4. Simulation started with building equipment module database which was handed to the Process Simulation. At this phase, a process was simulated at variable production rates which would ultimately result in multiple equipment modules at different sizes for each process unit. Additionally, reactor modules at bigger operating window were inserted into the equipment module database to evaluate how it impact the overall operating window of production. Next, the discrete market demand points were being simulated. During this, viable equipment-wise capacity expansion phases were moved to the Lifestyle Simulation. Result suggested that equipment-wise capacity expansion displayed superior performance followed by the line-wise capacity expansion strategy and the conventional design when assessed by NPV (net present value) and EAA (equivalent annual annuity). Overall, a step-wise capacity expansion utilizing modular equipment was judged to be a viable answer in view of uncertain market and production demands.



(a) conventional design (b) line-wise capacity expansion (c) modular equipment-wise capacity expansion

Fig. 4. Schematic illustration of conventional design, line-wise capacity expansion and modular equipment-wise capacity extension [51]

Teerasoponpong and Sopadang [57] also analyse small and medium-size company on their simulation-optimization approach for manufacturing capacity planning. The approaches applied in the study included an artificial neural network (ANN) for model simulation and data link identification, with the combination of genetic algorithm (GA) for resource configuration optimization. In this study, simulation approach begins with problem formulation to emphasize the relationship between the process parameters. There were both internal and external process parameters addressed in the simulation. Internal criteria included available equipment and staff, set up time, processing time, waiting time etc. External influences included demand quantity and available operation time. A synthesis dataset was generated which include of production yield, total operation time and total cost depending on the configurations of the manufacturing resources. Brute-force method was applied for identifying all conceivable parameter values in the created model. This study applied intelligent approach ANN for discovering the relationship between the resource configuration and production yield, cost and time. After that, genetic algorithm (GA) was applied to perform process parameters optimization. The recommended approach of configuration from the study may be applied as decision support system (DSS) for manufacturing capacity planning. Implementation of the simulation approach in pastry company indicated the growth in average yield at 6.86%, 14.34% decrease in average cost and reduction of 9.95% of labour cost.

For Make-To-Order (MTO) enterprises frequently cope with continuing capacity planning challenge. Wicaksono H and Ni T [58] designed an automated manpower planning model that assist in synchronization of capacity load for short to medium planning horizons. Validation was then done in an actual production unit at a German small MTO business that employ SAP (Systems, Applications, and Products in Data Processing) ERP (enterprise resource planning) in their operation. Several data pertaining to current and expected orders, purchasing lead times, manufacturing process and production routings were gathered from Manufacturing Resource Planning (MRP II) system; whereas ERP grabbed the data regarding human resources, machines and finance. For data extraction purpose, a unique Excel Macro was built as part of the planning tool. Those important capacity demands data were then pre-processed and translated into aggregate values, followed by presentation in a form of bar chart. Simulation was done in such way to remove or to add machine from the production line and observed the capacity load consequence. As a result, the created model which was pragmatic and personalized tool was able to allow the production planner to have appropriate time to alter capacity in short and medium planning horizons. In conclusion, Table 4 illustrates the overview of above-discussed literatures important to simulation-approaches in capacity planning.

Table 4
Summary of studies relating to simulation-approaches in capacity planning

Articles	Research Objectives	Techniques Utilized
Kumar and Nottestad [32]	Use of front-end engineering techniques to improve the decision-making processes related to capacity planning, capital equipment selection and the control strategies in a sequential plastic parts manufacturing line	Discrete-Event Simulation; Design of Experiment (DOE)
Niroomand *et al.,* [44]	To suggest optimal allocation of capacity investments at the tactical decision-making level	Mixed Integer Programming (MIP); Discrete-Event Simulation
Gómez-Rocha *et al.,* [25]	To minimize the total cost of aggregate production plan (APP); which include workers cost, inventory costs, backlogs and production cost for a Mexico's furniture company	Two multi-stage stochastic linear programming models
Lin *et al.,* [39]	To address the capacity expansion decision to meet the projected stochastic demands, by identifying the purchased amount of new auxiliary tools and expanded quantity of product group-specific capacity within a particular timeframe in the thin film transistor liquid crystal display (TFT-LCD) industry	Stochastic dynamic programming (SDP) model with an embedded linear programming (LP)
Renna [53]	To improve all the performance measures with controlled number of machines' reconfigurations.	Gale-Shapley model (a Game-Theory algorithm)
Diaz *et al.,* [22]	Reconfiguration of multi-part lines in reconfigurable manufacturing systems (RMS) to maximize throughput and minimize total buffer capacity simultaneously in handling fluctuating production volumes	A Simulation-Based Multi-Objective Optimization (SMO) – FACTS Analyzer
Lee and Charles [38]	To address a capacity expansion problem by integrating the perspective of marginal productivity factors in the model	Comparison of Basic Model, ULB Model, EV Model and SP Model
Radatz *et al.,* [51]	To find best strategy for equipment-wise capacity extension in chemical production plant	Process Simulation Lifestyle Simulation
Ziarnetzky and Mönch [61]	To address integrated production planning and capacity expansion problem for a simplified semiconductor industry	Discrete Event Simulation (DES)
Teerasoponpong and Sopadang [57]	To propose a solution for reducing the burden on SMEs in collecting and utilizing data for the planning of manufacturing capacity	artificial neural network (ANN) genetic algorithm (GA)
Wicaksono and Ni [58]	To implement an automated manpower planning model that help in synchronizing of capacity load for short to medium planning horizons for Make-To-Order (MTO) companies	Simulation using customized Excel Macro

Manufacturing sectors operate in dynamic and evolving environments, with fluctuating market conditions, technological developments and different sustainability standards. As such, it is vital to ensure that the simulation models developed for capacity planning decisions not only work well in the short term but also preserve their usefulness and accuracy over a long period. As such, study on the adaptability and endurance of these models in the face of evolving market trends, sustainability initiatives, and unforeseen shocks will contribute to a more thorough understanding of their practical utility. The lack of research that examine the long-term efficacy and sustainability of capacity planning simulation models presents a chance for academics to explore into this key element.

5. Conclusions

These reviews have successfully covered studies ranging from optimal capacity investments, stochastic demand management, manufacturing flexibility considerations, real option analysis, and reconfigurable manufacturing systems that proven to be able to provide valuable insights into addressing the complexities of capacity planning and decision making. Besides, the diverse range of simulation techniques and models discussed in these studies underscores the versatility of simulation as a problem-solving tool, adaptable to the unique needs and contexts of manufacturing companies, whether they are large enterprises or small and medium-sized businesses. This collection of studies underscores the crucial significance of simulation in aiding manufacturers in reaching improved consistency and effectiveness in capacity planning, thereby helping them navigate the ever-evolving terrain of modern manufacturing. Further study in this field may further deep dive into studies of the long-term performance and sustainability of the numerous constructed models. Besides, integrating of emotional engineering into capacity planning decision making framework can be a fascinating subject to be investigated in the future.

Acknowledgement
The authors would like to express our gratitude and appreciation to Fakulti Teknologi dan Kejuruteraan Industri dan Pembuatan, Universiti Teknikal Malaysia Melaka for the support extended in realising the success and smooth implementation of this project.

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