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Mathematical modeling of flexible production lines with different part types on unreliable machines by a priority rule

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Abstract *– In this paper, we offer an analysis and model of a manufacturing line that uses a priority mechanism to process various types of parts in faulty machinery. The manufacturing line comprises machines separated in a set order by storage rooms where components are fluxed. When it is possible, a machine works on the most important part first and only switches to less important parts if it is unable to produce the most important ones. Only one sort of function is required for each section. Because it is expected that the processing line machinery can handle a range of part types, switching from one kind of component to another will not result in any setup penalty. Only when unable to process higher priority parts owing to obstruction or hunger can the machines work on the lower priority parts. The machines function according to a fixed priority rule. The purpose of this study is to develop mathematical formulations and procedures for each kind of component in a flexible production line. In a variety of supply and demand scenarios, the multipart line's qualitative behavior is described.. To better understand the line, we devise decomposition equations and a solution technique to put them to use. With suitable line parameters, the method converges consistently. The findings of the decomposition were verified using simulations. The line's fascinating behavior may be seen in the system's study of many parameters.*

Keywords*– Flexible manufacturing systems (FMS), Mathematical modeling, Production lines.*

I. INTRODUCTION

Synchro Tandem manufacturing lines manufacture a wide variety of parts using unstable equipment, as described in this research, which includes a simulation and analysis of the system. The stock is stored in the machine buffers. Adaptability is defined as the ability for a machine to work with a wide range of various parts and to do so without incurring any additional setup costs.

Research in this area focuses on formulating and using mathematical models to evaluate manufacturing systems that process several component types. In other words, it is the objective of this article to answer the question, “What is to be expected of the flexible production line design for each part type?”

This document is about building an analytical model to correctly consider important system phenomena to assess genuine production lines.

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A. Motivation

In the mid-1960s, labor market competition intensified and costs became very important. But then quality came first, and as the speed of receipt became what customers needed, the job market became more complex. A new strategy was developed, the ability to improve the system based on customer needs. Companies had to adapt to the environment in all their work so that they were more flexible in their actions and satisfied in different segments of the labor market. Thus, the invention of FMS was associated with the pursuit of competitive advantage. First of all, FMS is production technology. Second, FMS is a philosophy. "System" is its keyword. Today, flexibility means producing at a reasonable price and improving products to the highest quality that can reach customers quickly.

There are three stages in production flexibility:

Step 1) Main flexibilities (Machine- Material transfer- Operations).

Step 2) System flexibility (Volume- Development- Determining the route-Process- Product).

Step 3) Overall flexibility (Program- Product- Labor market)

The concept of a flexible machining system (FMS) was first developed in the UK in 1960 under the name System 24 as a computer-controlled, always-on milling system. From the beginning, automation was emphasized instead of reorganizing the workflow. FMS now tends toward smaller species of traditional FMS called flexible production cells (FMCs). Today, two or more CNC machines comprise a flexible cell, and two or more cells comprise a flexible production system. Thus, a flexible production system (FMS) comprises several machine tools with tool transmissions and components such as robots. They are adjusted so that they can carry the same parts as they are designed and developed (Rastgar, Rezaean, Mahdavi, & Fattahi, 2021).

Since Flexible Manufacturing Systems (FMS) was developed in the 50s to offer a production line for the installed equipment and activities which could create multiple types of goods in one single factory, many industries have adopted them in current manufacturing lines (Browne, Dubois, Rathmill, Sethi, & Stecke, 1984; Gershwin, 1994). Now that robots and other forms of highly automated material handling are available, machines can easily switch between different product types. This flexibility was introduced to manufacture multiple types of items on the same production line (Gania, Stachowiak, & Oleśków-Szłapka, 2017; Hajduk et al., 2018; Homayouni & Fontes, 2019). For example, in high-tech sectors such as semiconductor memory chip and LCD panel manufacturing, single production lines have become commonplace.

The ability to respond quickly and flexibly to the requirements of consumers across a variety of product categories has lately supplanted cost as the fundamental metric of competitiveness. Because of the large capital investment in production lines, it is essential to understand and anticipate the complete behavior of the FMS manufacturing line (far over 5 billion dollars). Flexible manufacturing, on the other hand, has received less attention from researchers. Industry line designers lack the tools and methods to account for a production line's dynamic behavior while processing many component kinds. There is a requirement for production line analysis and intuition, as well as techniques for predicting the behavior of their systems and estimating their performance (Keshmiry Zadeh, Harsej, Sadeghpour, & Molani Aghdam, 2021).

B. Problem Definition

In the field of industrial competition between manufacturing companies, companies can compete that can accurately identify the factors and variables affecting their industry profession and after identifying them, implement a suitable solution to properly implement the factors affecting the currency markets. Among these effective variables, we can name the quality, the level of technology used in the product, the production and supply of products according to the needs of today’s customers, and so on.

Therefore, survival in a rapidly growing and changing world requires the right and timely decision. This decision is subject to several factors, including obtaining information, funding, ways to acquire new technologies, identifying obstacles to the implementation of these technologies, and so on. Also, due to the uncertainty in the current markets, making wrong decisions has caused heavy losses for companies and if it does not bankrupt them, it will push them to the brink of bankruptcy (Sharifzadegan, Sohrabi, & Jafarnejad Chaghoshi, 2021).

Towards the end of the twentieth century, mass production has given way to flexible production. In the present age, the face of life will change with the change in production methods. Flexible production has a different philosophy, in which the relationship between price, quantity, quality, and profit is established, which is different from previous ideas. Flexible manufacturing is a relatively new policy used by successful companies to develop and increase competition. It is said that the problem of lack of land is one of the reasons for the formation of a flexible production system.

The ability to create comparative and competitive advantage is a value in today’s dynamic and evolving industrial environment. Flexible production can be used to produce a variety of products tailored to customer needs. Workers respond to flexible production only when there is a sense of mutual commitment. It is undeniable that in no century has the volume and the speed of change in all areas of social, economic, cultural, and artistic life been so great.

A flexible manufacturing system (FMS) of a set of processing stations (mainly CNC machine tools) that are interconnected by an automated material handling and storage system and an integrated computer system. What gives it the name FMS is that it is capable of simultaneously processing several different types of NC-controlled components on different workstations. The initials FMS are sometimes used to describe the term flexible machining system. The machining process is currently the largest field of application of FMS technology (Heydarian & Ramezanian, 2021). However, the interpretation of FMS seems to be consistent in its broader sense, which encompasses a wide range of possible non-machining applications. Due to the need for increasing the expansion of flexible production lines, this study seeks to investigate and mathematically analyze flexible production lines in production systems.

In other words, mathematical formulations and methods for analyzing a production system processing more than one component type are developed in this study. The complexity and unpredictability of production systems make it difficult to analyze system behavior and evaluate system performance. Methodologies such as real-world experimentation, simulation, and analytical methods are all part of a systematic approach. To conduct real-world tests to build a new manufacturing system, real-world experimentation is impossible. A manufacturing line is typically too costly and time-consuming for testing, even if it's accessible.

To forecast the behavior of manufacturing lines, simulation is often employed in the industry. If you're looking to evaluate a single final design in great detail, this tool might come in handy. Analytically useful simulation results, on the other hand, take a considerable amount of computation and modeling time. System performance can be quickly assessed using analytical models, but they are time-consuming to build. Analytical procedures are frequently more efficient and less costly than simulations, but they're also more error-prone since they abstract reality. This effort focuses on creating an analysis model that accurately evaluates real manufacturing lines (Alamiparvin, Mehdizadeh, & Soleimani, 2021).

Research limitations include lack of access to strategic information, lack of accurate information, and lack of familiarity of the majority of people working in the industry with the flexible production system so the work of data collection and mathematical modeling has been somewhat difficult.

C. Conceptual Framework

The following figure shows the conceptual framework of the research. As can be seen in the figure, the problem of flexible production includes a wide variety of internal and external variables that by controlling and modeling each variable can be identified and analyzed the behavior of the system. Of course, as mentioned in the introduction, the scope of this paper is the mathematical modeling of the flexible production line, regardless of the variables that affect it. In other words, in this paper, only the flexible production line is analyzed from a mathematical point of view.

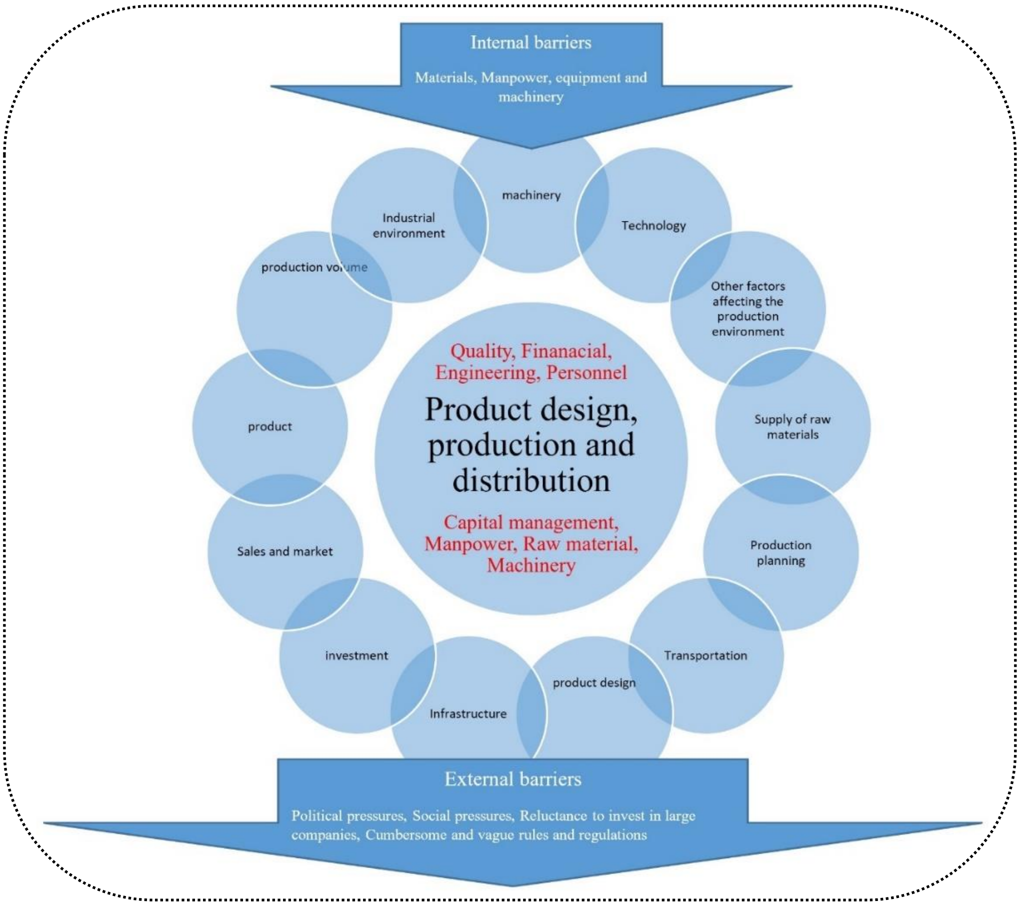

Fig 1. Conceptual framework of the paper

II. LITERATURE REVIEW

As a Markov process, Buzacott modeled a one-finite-buffer two-machine production system. The concept assumed that machines were not dependable and that they were susceptible to operational failures (ODFs). The model also assumed that both machines had identical and predictable operating times. Geometrically distributed failure and repair timeframes (J. A. Buzacott & Shanthikumar, 1993). Buzacott and Hanifin utilized data from the Chrysler Corporation to bolster their ODF assumption. These data demonstrated that the overwhelming majority of failures were caused by ODFs. (J. A. Buzacott & Hanifin, 1978). In general, the production lines are not analytically tractable longer than two machines. However, most companies have numerous machinery manufacturing lines. The decomposition that Gershwin presented is one technique that has proven realistically durable for manufacturing lines with endless buffers and unlikely equipment. This model assesses the tandem arrangement of the line’s throughput and average buffer levels (Gershwin, 1987, 1994). This concept was then extended to Gershwin's assembly/disassembly network. Under the same premise, researchers have proposed a decomposition technique for lines with a loop setup (Beier, 2017; Papadopoulos, Li, & O'Kelly, 2019; Yadav & Jayswal, 2018). All reported models, however, were restricted to one particular sort of component. The articles cited above conducted several surveys in the field of FMS. Only a few of them have addressed all of these difficulties in a single work. This document categorizes several studies in the field of FMS based on the approach used to simulate FMS. This page defines and offers Petri Net, hierarchical, simulation, mathematical programming, and hierarchical models.

A. Mathematical models

In general, mathematical models make use of mathematical concepts to address a specific issue. When making decisions on input and output parameters, they are a huge help to the planner. Helps to predict the behavior of a specific model. These models have the drawback of being difficult to understand by other users. Long and time-consuming models. The following are a few papers on FMS mathematical modeling:

FMS properties were examined and a model for calculating system capacity was created by Buzacott and Shanthikumar (J. A. Buzacott & Shanthikumar, 1980). Workload distribution, routing, and shared storage all have their benefits outlined. Material handling system delays were included in the developed model. After considerable consideration, it was concluded that a production capacity model could be utilized to calculate system tasks for particular arrival rates. Different non-linear mixed integer programming algorithms were utilized by Stecke to solve the FMS loading and grouping issue (Stecke, 1983). Grouping machines and minimizing the mobility of components were two of the goals of the project.

A genetic algorithm (GA)- based heuristic was devised by Tiwari and Vidyarthi (Tiwari & Vidyarthi, 2000), to minimize system unbalance and maximize throughput in the situation of a random FMS.

To deal with more complicated variables, Kumar et al. used an extension of the basic genetic algorithm to create a genetic algorithm based on constraints by providing three new genetic operators, based on initialization, crossover, and mutations (A. Kumar, Tiwari, Shankar, & Baveja, 2006).

Sujono and Lashkari's approach employs integer programming to select machines, assign operations, and choose the suitable material handling system (Sujono & Lashkari, 2007). Ahkioon, Bulgak and Bektas cellular manufacturing systems employed mixed integer programming (MIP) to address various parts of production planning and control problems (Ahkioon, Bulgak, & Bektas, 2009).

He, Stecke, and Smith looked at the sequencing and scheduling of components in a fast-moving mass-production system (FMS) under dynamic conditions (He, Stecke, & Smith, 2016). Part sequencing was done using 9 machine and robot scheduling rules and a state-dependent algorithm. The simulation tested how algorithm and scheduling rules affect FMS performance. The earliest due date is the best scheduling approach for robots and machines. Changes to robot scheduling regulations affect performance.

When it comes to analyzing manufacturing systems, Erdin and Atmaca recommend that thorough attention be paid to all levels of the system (Erdin & Atmaca, 2015). Physical, analytical, or simulation approaches were used. When it came to determining the number of workstations needed, calculating manufacturing lead time and utilization, grouping components, forming production cells for the grouped parts, and arranging and securing the workstations in those cells were all part of this process.

B. Artificial intelligence models

FMS design and planning concerns were mostly overcome by this modeling method. Artificial intelligence is a technology that involves putting human intellect into a computer system. There was an interaction between internal and exterior aspects of the FMS database produced by Sheinin and Tchijov (Sheinin & Tchijov, 1987).

An Intelligent Decision Support System (IDSS) based on simulation was developed by Buzacott for the real-time control of flexible manufacturing systems (FMSs) (J. Buzacott, 1982). An expert system based on rules was used to develop a strategy. An IDSS and a simulator module were used to create the new controller. Finally, the controller's performance was proven by completing a benchmark test. An FMS grouping issue was solved with the use of IDSS, according to Suresh (Suresh, 1990). IDSS was created by Shirazi, Mahdavi, and Solimanpur to regulate FMS in real-time (Shirazi, Mahdavi, & Solimanpur, 2012). Online information regarding FMS state and symptoms may be used to produce control rules for flexible operation assignment and scheduling of multifunctional machining centers.

When it comes to priority analysis and routing of incoming work, Bramhane, Arora, and Chandra focused their attention on that (Bramhane, Arora, & Chandra, 2014). The machine was outfitted with a variety of tools and tool magazines to maximize system use and throughput. An adaptive neuron fuzzy inference system that uses the slack per remaining operations (S/RO) parameter to determine the priority of incoming workloads was created.

C. Hierarchical models

Mazzola, Neebe, and Dunn presented a hierarchical production planning approach for integrating a production schedule with a closed-loop material requirement plan (MRP) (Mazzola, Neebe, & Dunn, 1989). Problems with grouping, planning, loading, and scheduling were all addressed in the model. Systematic spillage of problematic batches eventually resolved the circumstances for the FMS rough-cut capacity planning challenge. As a result, the material requirement planning system was involved, as well as the FMS system's limitations. The authors of Das, Baki, and Li focused on the grouping of components, the loading of machines, and the allocation of tools to these systems (Das, Baki, & Li, 2009).

D. Multi-criteria decision-making (MCDM) models

This method is mostly used when a system has to choose the best choice from a given list. The MCDM approach uses a ranking process to determine the best solution for a particular issue, then narrows the list of possible solutions. The first stage is to build a hierarchical framework for the issue and then rank the criteria and solutions inside it. Many researchers have contributed to the process of selecting the best FMS. The analytic hierarchy process (AHP) was utilized by Wabalackis to solve this issue (Wabalickis, 1988). Shang and Sueyoshi used AHP, simulation, and accounting to pick FMSs throughout design and planning. (Shang & Sueyoshi, 1995).

To be considered for FMS, you must be Rao (Venkata Rao, 2008). There are nodes and edges added to represent distinct properties and the connection between them in this network. In addition, the suggested technique was compared to the results of AHP and Analytical Network Process (ANP) methodologies. The method's technique had a flaw since it wasn’t appropriate for challenges with a greater number of criteria. To find the optimal FMS for a certain manufacturing company, Chatterjee and Chakraborty investigated six preference ranking approaches (Chatterjee & Chakraborty, 2014). The six techniques utilized to rate the alternatives were EVAMIX, COPRAS, ARAS, PROMETHEE II, ORESTE, and OCRA. The AHP technique was used to determine the relative importance of each criterion in each approach. Finally, we used Spearman's rank correlation coefficient and Kendall's coefficient of concordance to compare the order in which each approach was ranked. The ORESTE approach was shown to be the most effective way for rating preferences. For finding the optimum dispatching rule, Kashfi and Javadi employed fuzzy AHP and fuzzy TOPSIS methods (Kashfi & Javadi, 2015).

E. Petri Nets models

In a deadlock, components wait for other parts to free up resources before they do so themselves. In any system, this is a bad thing. There was a usage of the PN model for deadlock avoidance in FMS by Viswanath, Narahari, and Johnson (Viswanadham, Narahari, & Johnson, 1990). The technique of deadlock avoidance was implemented using a generic PN model based on an online controller. The model was able to foretell future changes to make wise decisions about how to allocate resources. Static resource allocation rules were also employed in the PN model's reachability graph to avoid deadlocks. Finally, a path evaluation of the PN model’s reachability graph proved beneficial for a small system. A deadlock-free scheduling approach incorporated into a heuristic search algorithm was used by Lei et al. to reduce the system's makespan (Lei, Xing, Han, Xiong, & Ge, 2014). The scheduling process made use of the PN model reachability graph, while the search process made use of heuristic functions, as well as the one-step look-ahead approach, which tested to see whether the newly created state was safe.

As the cost of installing FMS necessitates a large investment, adequate planning must be done in the choosing of FMS type. Before deployment, a comprehensive feasibility and performance assessment based on the PN model took into account a wide range of FMS-related technical, economic, design, managerial, and social aspects. The Petri Nets model was utilized by Basak and Albayrak to regulate FMS (Başak & Albayrak, 2015). Methods for modeling performance and controlling production have been presented using an object-oriented PN approach. There were m, $(n+1)$ variables in the linear programming (LP) problem based on the number of locations in the marked graph of the model and the number of transitions, respectively, in the PN model. Using CPN search, Baruwa and Piera was able to find optimum solutions to the state explosion issue in reachability graphs (Baruwa & Piera, 2015). The reachability graph's structural equivalence was violated, which lowered the amount of memory the model needed. For FMS of varied lot sizes, structural equivalence was shown via the identification of duplicate states.

F. Simulation models

Models for simulating an issue are known as simulation models. As a result, it is possible to test the model's performance under various settings without actually doing tests. You may cut costs and resources by using this strategy.

According to Matsui et al., FMS performance was examined to maximize system throughput (Matsui, Uehara, & Ma, 2001). Analysis and simulation of queuing network behavior and throughput first utilized system behavior and throughput in both processes.

The design issues were then taken into account quantitatively for both fixed and dynamic routing. Local buffers and routing probability requirements were found to be important in the construction of a successful FMS. Ali and Wadhwa studied a variable system of integrated production under different routing, pallet, machine loading, and component sequencing regulations (Ali & Wadhwa, 2010). To find the most significant factor, simulation and Taguchi's approaches, coupled with ANOVA, were used.

Singholi, Ali, and Sharma investigated the impact of loop-type FMS machines and routing flexibility on performance (Singholi, Ali, & Sharma, 2013). Taguchi's experimental design was used to provide a framework for the presentation. Makespan, average waiting time, and average utilization were all taken into account while evaluating performance. Additionally, the effect of control rules on performance was examined. FMS performance was affected primarily by the number of pieces in the system and the degree of routing flexibility.

The Taguchi approach was used by Singholi to examine the impact of routing and machine flexibility on the FMS in various configurations (Singholi, 2015). The impacts of buffer delay in the FMS under consideration were further studied using various scheduling rules and the number of pallets. It was shown that the number of pallets and the flexibility of the route are the two most important variables in determining buffer delays. There is a simulation-based technique for computing assembly line production plans in a multi-stage production system developed by Gyulai, Pfeiffer, and Monostori in 2016 (Gyulai, Pfeiffer, & Monostori, 2017). Data from the lower-level shop floor was used to generate the plans.

Results for production lines are summarized in the following table using a variety of modeling methodologies to demonstrate the FMS challenge. It is clear from the table that different approaches to FMS modeling may be employed in various circumstances.

Table I. Authors' FMS modeling techniques and issue description

Approach	***Author's***	***Problem description***	***Methodology***
Mathematical	Stecke (Stecke, 1983)	Machine-grouping issue	Mixed-integer nonlinear programming
	Lashkari et al. (Lashkari, Dutta, & Padhye, 1987)	Loading issue	LIP method
	Tiwari and Vidyarthi (Tiwari & Vidyarthi, 2000)	Random FMS loading	Genetic algorithm (GA)

	Bokhorst et al. (Bokhorst, Slomp, & Suresh, 2002)	System investment analysis	Integer programming method
	Ahkioon et al. (Ahkioon et al., 2009)	Designing CMS	Integer programming method
	Subbaiah et al. (Subbaiah, Rao, & Rao, 2009)	Machine and two AGV scheduling	Mixed-integer nonlinear programming
	Kumar et al. (M. Kumar, Janardhana, & Rao, 2011)	Scheduling machines and AGVs	DE algorithm
	He et al. (He et al., 2016)	Sequencing and scheduling of parts	State-dependent sequencing algorithm
	Lechuga & Sánchez (Lechuga & Sánchez, 2018)	The primary optimization strategies utilized in FMS issues are described and analyzed in this article. The findings are based on a random sampling of more than 100 FMS-optimization-related publications published between 1986 and 2018.	Stochastic Approach
	Dyadichev et al. (Dyadichev, Stoyanchenko, & Dyadichev, 2020)	To find the traffic structure in flexible manufacturing systems, the study introduces a set of mathematical models that may be used to find an efficient traffic structure. The combined technique, which blends imitation and analytical modeling, is the foundation of the established methodology.	searching for a rational AMS traffic structure with the combined method, which combines imitating and analytical modeling
	Jahed & Tavakkoli Moghaddam (Jahed & Tavakkoli Moghaddam, 2021)	Using a scheduling issue and a material handling system as an intelligent transportation system, this research develops a novel mathematical model for a manufacturing system (AGVs).	mixed-integer linear programming (MILP)
	Jerbi et al. (Jerbi, Hachicha, Aljuaid, Masmoudi, & Masmoudi, 2022)	Supporting FMS diagnostics and design by understanding the dynamics of stochastic system performance.	multi-objective simulation–optimization (MOSO) Goal Programming (GP) and Desirability Function (DF)
Artificial Intelligence (AI)	Suresh (Suresh, 1990)	FMS Intelligent grouping	decision support system (IDSS)
	Chan, Jiang, and Tang (Chan, Jiang, & Tang, 2000)	FMS design	IDSS
	Shin et al. (Shin, Park, & Kim, 2011)	FMS Planning	Evolutionary multi-objective algorithm
	Shirazi et al. (Shirazi et al., 2012)	FMS control	IDSS
	Bramhane et al. (Bramhane et al., 2014)	Analysis and routings of a variety of incoming jobs in FMS	Adaptive neuron fuzzy inference system
	Li (H. Li, 2016)	improve the performance of a production system, reduce the electricity consumption in an automation system	Machine learning algorithms classification algorithm and the Q-learning algorithm

	Bakakeu et al. (Bakakeu et al., 2018)	best control strategy for the operation of the flexibly programmable machine in an electrical micro-grid with substantial electricity price volatility	deep reinforcement learning
	Wan et al. (Wan et al., 2020)	This article focuses on the application of artificial intelligence (AI) in the manufacture of personalized goods (CM). The design of an AI-driven smart factory is shown. Construction of a flexible production line and demonstration of intelligent manufacturing equipment and intelligent information interaction.	AI-assisted CM
	Kocher et al. (Köcher et al., 2021)	A flexible manufacturing environment is described in detail in this study. We'll next go through a variety of existing Artificial Intelligence techniques that may help us meet these goals. Consider both planning algorithms and the models of production systems that may be used as inputs to these algorithms to get the best results.	symbolic AI planning and machine Learning
	Li et al. (J. Li, Pang, Zheng, Guan, & Le, 2022)	Automated assembly motion planning and a production line monitoring system were proposed as part of a systematic approach.	Reinforcement learning, Digital twin
Hierarchical	Das et al. (Das et al., 2009)	Loading and grouping	Operation sequencing technique
	Morvan et al. (Morvan, Dupont, Soyez, & Merzouki, 2012)	presents a formal approach for specifying, modeling, and validating multi-level complicated hierarchical systems.	specification of hierarchical complex systems, holonic multi-agent systems (HMAS)
	Singh & Khan (Singh & Khan, 2016)	Heuristic-mathematical loading issue modeling using machine processing time as key input is presented in this study. The goal of this research is to find a solution to a real-world machine loading issue by reducing the calculation time required by the FMS.	Realistic modeling
	Chawla et al. (Chawla, Chanda, & Angra, 2019)	This research investigates AGV multi-objective scheduling to balance AGV workload and decrease AGV trip time in the FMS at the same time. The results are shown below.	Grey wolf optimization algorithm (GWO)
	Toth et al. (Tóth & Kulcsár, 2021)	For this work, an optimization model is presented for tackling an integrated issue of planning and control. To manage a team of highly trained manual employees and establish comprehensive production plans for a complicated manufacturing system,	Search algorithms
Multi-Criteria decision Making (MCDM)	Buyurgan et al. (Buyurgan, Saygin, & Kilic, 2004)	Machine tool selection	Life over size method
	Yurdakul (Yurdakul, 2004)	Machine tool selection	AHP and ANP
	Ayag and Ozdemir (Ayağ & Özdemir, 2006)	Machine tool selection	AHP with fuzzy logic

	Low et al. (Low, Yip, & Wu, 2006)	FMS scheduling problem	Combination of tabu search and simulated annealing method
	Cimren et al. (Çimren, Çatay, & Budak, 2007)	Machine tool selection	DSS with AHP
	Buyurgan and Saygin (Buyurgan et al., 2004)	FMS scheduling and routing issues	AHP
	Yazgan et al. (Yazgan, Boran, & Goztepe, 2010)	Selection of dispatching rule	ANP
	Taha and Rostam (Taha & Rostam, 2012)	CNC machine selection	DSS with AHP and PROMETHEE
	Kashfi and Javadi (Kashfi & Javadi, 2015)	Selection of dispatching rule	Fuzzy AHP and fuzzy TOPSIS
	Prakash et al. (2018) (Prakash, Singhal, & Agarwal, 2018)	The management of the example firm should be assisted in the selection of the most efficient production system by an integrated fuzzy-based multi-criteria decision-making framework (F-MCDM)	fuzzy-based multi-criteria decision-making (F-MCDM)
	Yadav, A., & Jayswal (2021) (Yadav & Jayswal, 2021)	By applying basic calculations that may save money and time, this research attempts to build an approach for determining the ideal experiment level	Combining Shannon entropy and weighted aggregated sum product assessment (WASPS)
	Samala et al. (Samala, Manupati, Machado, Khandelwal, & Antosz, 2022)	Throughput Rate, Throughput Time, System Usage, Availability, Average Stay Time, and Maximum Stay Time are studied as real-time disruption diagnostics of industrial systems	integrated MCDM-TOPSIS based simulation approach
Petri Nets	Viswanadham et al. (Viswanadham et al., 1990)	Prevention of deadlock condition	Generic PN model based on online Controller system
	Raju and Chetty (Raju & Chetty, 1993)	Modeling, simulating and evaluating FMS	Performance Priority nets
	Shah et al. (Shah, Bohez, & Pisuchpen, 2011)	Design and development of tool sharing control	Coloured Petri Nets (CPN)
	Basak and Albayrak (Başak & Albayrak, 2015)	FMS control	Petri nets
	Chen et al. (Chen, Li, Al-Ahmari, Wu, & Qu, 2017)	A set of recovery transitions is added to Petri nets in this study to cope with deadlocks. This work adds transitions to a net model to recover all deadlock marks, in contrast to standard deadlock control approaches that deploy control locations for a net model to be controlled	integer linear programming problem (ILPP)
	Bashir & Hong (Bashir & Hong, 2019)	A huge Petri net model for flexible manufacturing systems has been designed using a novel way of constructing a global controller for decentralized systems	Petri nets

	Hu et al. (Hu et al., 2020)	Flexible manufacturing systems (FMSs) with shared resources, route flexibility, and stochastic arrivals of raw goods are addressed in this research using the deep Q-network (DQN), a successful DRL approach	Petri nets, Deep reinforcement learning, Graph convolutional networks
	Lin et al. (Lin et al., 2022)	There were no deadlocks in this research, and the objective of lean production was achieved via the use of Petri net models, analysis, and modeling.	Petri nets
Simulation	Matsui et al. (Matsui et al., 2001)	Evaluated FMS performance	The objective of maximizing throughput
	Chan (Chan, 2001)	Route levels, pallet number, and dispatch rule affect FMS performance.	Consideration of makespan, lead time, and machine utilization
	Cheng and Chan (Cheng & Chan, 2011)	Optimized part input sequence	Based on the highest total slack time
	Shivhare (Shivhare & Bansal, 2014)	Machines and AGV Particle	swarm optimization technique
	Gingu and Zapciu (Gingu & Zapciu, 2014)	Optimization of FMS performance	Delmia Quest simulation technique
	Kumar (R. Kumar, 2016)	FMS performance affected by flexible routing and part-mix ratio	ARENA software
	Arshad et al. (Arshad, Milana, & Khan, 2016)	FMS performance affected by scheduling rules and layout	ARENA software
	Rybicka et al. (Rybicka, Tiwari, & Enticott, 2016)	Sequence, machines, and pallets affect FMS performance	WITNESS simulation software
	Gyulai et al. (Gyulai et al., 2017)	Calculation of production plans	Simulation model
	Florescu et al. (Florescu, Barabaş, & Sârbu, 2017)	Analysis of FMS performance	ARENA software
	Mahmood et al. (Mahmood, Karaulova, Otto, & Shevtshenko, 2017)	Integrated FMS performance analysis	modeling technique
	Florescu et al. (Florescu & Barabas, 2020)	Flexible manufacturing systems are discussed in this study to determine the best possible design for their material flow. To simulate and optimize the flow of materials in sophisticated production systems, the study's findings provide an answer.	Simulation model
	Daniyan et al. (Daniyan et al., 2021)	Proposals include an FMS that includes the assembly line, lean manufacturing, logistics, and quality control. During the Anylogic 8.2.3. software simulation, a framework for the implementation of the FMS was developed.	Anylogic software
	Hamasha et al. (Hamasha, Hamasha, Aqlan, & Almeanazel, 2022)	Flexible manufacturing cells (FMCs) are tested in this article using a Markovian model. A conveyer belt, a robot, and n machines are all included in the FMC under consideration.	Simulation with Markov chain

	Rani et al. (Rani, Jain, & Angra, 2022)	In a stochastic and dynamic (SCDM) manufacturing setting, this study examines the impact of routing flexibility on order release rules in a flexible job shop.	Simulation model

A. Review of the single-part processing lines

Machinery and buffers are the foundation of a manufacturing line. To illustrate a single item type processing procedure, Figure 2 shows an assembly line (Gershwin, 1994). Pictures of machines and buffers are shown in the illustration using squares and circles, respectively. The processing unit, which is designated by the letter *M*, is used to process components. In-process inventories, or WIP in-process, are held between the machines with the buffers marked in the letter B. In the model, the buffer space is supposed to be limited. Some component goes linearly through the machines and buffers because it starts at the first machine and is then delivered immediately after the process is completed in the first machine to the next downstream buffer. The second and third machines will then take over the loading process. Parts in the model are anticipated to go from the initial machine to their ultimate destination. The line does not have a re-entry flow, components are never destroyed. Consequently, when a piece enters machine M_1, it travels onto $B_1;M_2;B_2;M_3$, and finally onto M_K, then leaves the line.

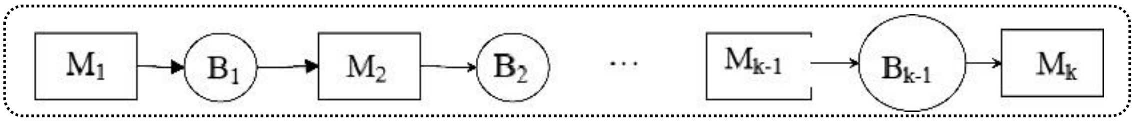

Fig 2. Processing a single item type on a manufacturing line

This time, we're counting on the manufacturing times of each machine to be predictable, identical, and in perfect unity. Despite this, machines are prone to breakdowns, and the number of breakdowns and the number of repairs required aren't necessarily equal. Additionally, the model implies that the machines have functional defects, which means that they can only fail if they work on a component. The machines are also believed to have spread up and down time geometrically. That is to say, each machine Mi in a given time step has a set probability pi that it will fail if it operates on one part and a defined probability ri that if it is down, it gets repaired.

Ni and ni(t) stand for the buffer size Bi and the buffer level at time t, respectively. For any time t, it is expected that the buffer will be $0 \leq n_i(t) \leq N_i$. Keep in mind that no two buffers may have the same size. Because of a blockage (i.e. ni = Ni), or because it is starving (i.e. ni = 0 in the current line setup), a host may be left inactive. Note that a machine that does not process a part owing to a malfunction is not as idle as a result of hunger or obstruction. When a computer is hungry or blocked, it has to cease processing, even if it is running and working.

B. One-Buffer Building Block for Two Machines

One of the most often asked questions in the study of the production line is "What is the speed of production?", "Is there a bottleneck machine and Which one?", and "How much money is at stake?". The answer to these issues is not easy and it may not be feasible to provide accurate responses to the general situation. An exact analysis is nonetheless achievable for a tiny system. Think about the system shown in Figure 3, which consists of two computers and a buffer. There is a finite N-size buffer between the machines. In this line, M^u denotes the first machine as the upstream machine, while M^d refers to the second machine as the downstream machine. The lengthy production line likewise applies to this line with all the assumptions mentioned. That is to say, the machines function at the same pace and can only be down if they work partly. When the machine Mu processes a part, it can fail, and it can be fixed with the probability of r^u when it is down. M^d also contains pd and r^d machine characteristics. Let us mark the M^u machine's status.

Let us define α^u to be 1 if M^u is up and $\alpha^u$to be 0 if M^u is down. Likewise α^d is the status of the M^d machine indicates. The buffer size is N and so the buffer size n meets $0 \leq n \leq N$. Then you may properly define the condition of the two-machine buffer line as $s = (n,\alpha^u, \alpha^d)$. Let E^u be the probability to participate M^u in a certain timeline, and E^d be the probability to participate M^d in that timeline. The amounts of $r^u; p^u; r^d, p^d$, and N are defined. Again, no portion in the center of the line is assumed, i.e. when a part enters M^u, the piece leaves M^d always. Thus $E^u = E^d = E$, where E is considered the line's production or output rate. In other words, E is the probability to generate one component at any time. E is also the output or throughput rate, as the operating duration is 1.

A discrete-time, discrete-state Markov process with accurate production rate and average buffer level data may also be generated to model this single-buffer two-machine system (Lechuga & Sánchez, 2018; Ram & Goyal, 2018). Additional performance metrics such as P_b's probability of blocking M^u and P_s's probability of starving of M^d can be assessed.

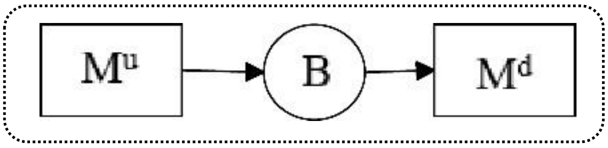

Fig 3. Two-machine one-buffer building block

C. Decomposition

Analytically, it is impossible to trace lines greater than two machines. A means to analyze a longer production line is needed since most facilities have several equipment manufacturing lines. It may not be feasible to develop a method for the precise evaluation of long-line solutions; an approach to the solution is thus helpful. Decomposition is one approach that has shown to be resilient, which approximates correct performance metrics for lengthy lines with unreliable equipment and finite buffers (Barzanji, Naderi, & Begen, 2020; Cochran, Foley, & Bi, 2017; Koren, Gu, & Guo, 2018). This procedure divides the lengthy production line into one-buffer tractable double-machine manufacturing lines known as the construction blocks.

A longer line's performance characteristics may be estimated by comparing them to those of the individual construction components. Building blocks are assembled into a finished product once they have been tested.

III. IDLE FAILURES ON TWO SEPARATE PRODUCTION LINES

Idleness Failure

When a nearby machine fails, it's known as a local failure mode. When a non-buffer machine fails, this is referred to as a remote failure mode. If the machines in this model aren't stopped or hungry, they may nonetheless fail. This two-machine line is a building block with an idleness failure because it may fail if one of the machines is idle, hanging, or obstructed. To understand why the failure mode has shifted, examine the following circumstances.

1. $M_{i'}$ lost.

2. M_i is blocked $i < i'$.

3. M_i begins to process type 2 parts.

4. M_i flops.

In the remote failure mode, if the downstream machine $M^d(i-1;1)$ fails, M_i will be blocked in Type 1. M_i prioritizes Type 2 components. Mi fails type 2. $M^d(i-1;1)$ changes to a new failure mode. Failed mode shift.

Two noteworthy findings are the shifts in failure modes. In the first place, only a failure mode that is closer to the observer may alter. When machines fail to start, they often spread to the observer because of a lack of food or an obstruction.

A. Transition Equations

Transient states

In a constant state, a two-machine line is unlikely to be in a transient state. As idleness is considered, the transient states are lower than those of Gershwin and Tolio. Those are temporary statements:

$P(0, \gamma^u, \Delta_l^d)$ and $P(0, \gamma^u, \gamma^d)$: At this point in a time step when the upstream machine is operational, the buffer will include a component that was placed in place when this time step began. This state cannot be arrived to through a transition.

$P(N, \Delta_j^u, \gamma^d)$ and $P(N, \gamma^u, \gamma^d)$: The buffer always contains fewer than N parts at the conclusion of a step because it eliminates a part whilst the downstream machine is running. Those conditions have not been altered by a transition.

B. Non-transient states

The state when the buffer is satisfied $2 \leq n \leq N$ is an internal state. If the upstream machine is repaired in failure mode *j*, the system may go from $P(n, \Delta_j^u, \gamma^d)$ to $P(n, \Delta^u, \Delta^d)$, but the downstream machine remains low. The likelihood of this happening is $r_j^u(1-P^d)$. As downstream mode *j* and *l* engines are serviced following upstream mode *j*, the likelihood of switching from$P(n, \Delta_j^u, \Delta_l^d)$ to $P(n, \gamma^u, \gamma^d)$ is $r_j^u r_l^d$ increased. In the same way, the possibility of a machine swap exists both upstream and downstream. The possibility of transitioning from non-transient states is now eliminated.

The first equation is, therefore:

$$P(n, \Upsilon^u, \Upsilon^d) = \sum_{j=1}^{J} \sum_{l=1}^{L} P(n, \Delta_j^u, \Delta_l^d) r_j^u r_l^d + \sum_{j=1}^{J} P(n, \Delta_j^u, \Upsilon^d) r_j^u (1-P^d) \tag{1}$$
$$+ \sum_{l=1}^{L} P(n, \Upsilon^u \Delta_l^d)(1-P^u) r_l^d + P(n, \Upsilon^u \Upsilon^d)(1-P^u)(1-P^d)$$

C. Performance Measures

Throughput, average buffer level, hunger probability, and blocking probability are all key performance parameters in a two-machine line.

Efficiency

The upstream machine's throughput is likely to work in *t+1* and not blocked at *t*. That is,

$$E^u = Pr[\alpha^u(t+1) = \Gamma^u \cap n(t) < N] \tag{2}$$

The machine's downstream power will probably work at time t+1 and not run out at time t. That is to say,

$$E^d = Pr[\alpha^d(t+1) = \Gamma^d \cap n(t) > 0] \tag{3}$$

Note in (2) that both time t+1 and time t is part of this expression. We shall make sure that events that occur at step t are written (2) as regards occurrences that take place completely at step t. In this way, we can fully reflect the state probabilities that are defined just once, for the production rates of the upstream machine.

D. Probability of blockage, hunger, and average buffer level

The average buffer level is indicated by

$$\bar{n} = \sum_{n=0}^{N} nP(n, \Upsilon^u, \Upsilon^d) + \sum_{j=1}^{J} \sum_{n=0}^{N} nP\left(n, \Delta_j^u, \Upsilon^d\right) + \sum_{l=1}^{L} \sum_{n=0}^{N} nP(n, \Upsilon^u, \Delta_l^d) +$$
$$\sum_{j=1}^{J} \sum_{l=1}^{L} \sum_{n=0}^{N} nP(n, \Delta_j^u, \Delta_l^d) \tag{4}$$

Ps, the downstream machine, is likely to be hungry since the machine is ascending and there is no buffer. This is what happened as a direct consequence of

$$P_s = P(\alpha^u = \Upsilon^u, \alpha^d = \Delta_l^d, n = N) \tag{5}$$

The probability that the upstream is blocked, referred to as P_b, is the probability of the machine up, and of the mid-buffer being complete. That's what it says

$$P_b = P(\alpha^u = \Delta_j^u, \alpha^d = \Upsilon^d, n = 0) \tag{6}$$

E. Solution Algorithm

In this part, we are proposing an approach for a numerical solution for the resolution of the transitional equations in Section 3.1. We denote the number of states by η and it is

$$N = (N + 1)(J + 1)(L + 1) \tag{7}$$

Where J and L are respectively the total numbers of M^u and M^d down states. The system has a constant state transition equation

$$p = Ap \tag{8}$$

$$v^T p = 1 \tag{9}$$

where

p is an unknown n-vector.

A is an $\eta \times \eta$ matrix. The rank if A- I is $\eta \times \eta$.

v is an η -vector, each of whose elements is 1.

Transition equations are A. Markov's continuous probabilities are p and A. Iterate to solve linear equations.

$$p(k + 1) = Ap(k) \tag{10}$$

Where p(0) is selected to meet (9), until p(k) is converging. In this situation, a criterion such as practical convergence is defined

$$\delta_i(k + 1) = |p_i(k + 1) - p_i(k)| < \varepsilon \tag{11}$$

for some suitable ε.

Matrix A has a significant percentage of zeros. Matrix A is shown in illustrative form in Figure 4. One and zero are the only nonzero integers in this matrix's nonzero block. The bulk of components are zero, as seen in the graph. The issue may be solved numerically by taking use of sparsity.

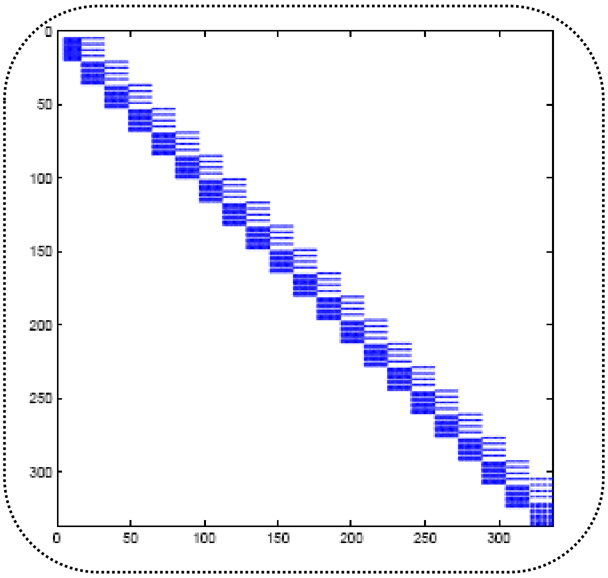

Fig 4. J = 3 and L = 3 is an example of a sparsity pattern

IV. General decomposition

The decomposition equations for a three-part manufacturing line may be applied for a multi-part line. However, state classifications used throughout the building blocks allow for generalization and application of the equations across multiple part types. An overview of the general decomposition is presented here using the equations from the preceding section.

A broad notion of decomposition is presented in this section. The total number of sorts of components indicated by *Z* for the general flexible line processes. We let *j* become the index of a certain sort of component in this section. The breakdown has 3 cases: highest priority (j=1), intermediate priority (*j=2,...,Z*), and lowest priority (*j=Z*). These three types of equations are almost comparable. We describe Category 1 of these equations hence for contraction reasons.

The machines in the basic components for all parts have the same amount of up and down states and Markov transition structure, no matter how many machines are in a line or how many part kinds there are. Comparing equations from various component types shows similarities. These values depend on neighboring and above/below sections. Short FMS breakdown equations are now available.

Flow re-start

$$\begin{aligned} &r^d(i,1) = r_{i+1} \\ &r_2^d(i,1) = (1 - q^u(i+1{,}1))R^d(i+1{,}1)) \\ &r_3^d(i,1) = r_{i+1}R^d(i+1{,}1) \\ &r_1^u(i+1{,}1) = r_{i+1} \\ &r_2^u(i+1{,}1) = (1 - q^d(i,1))R^u(i,1) \\ &r_3^u(i+1{,}1) = R^u(i,1)r_{i+1} \end{aligned} \tag{12}$$

Failure mode change

$$\begin{aligned} &z_{1,2}^d(i,1) = 0 \\ &z_{1,3}^d(i,1) = 0 \\ &z_{2,1}^d(i,1) = q_1^u(i+1{,}1)R^d(i+1{,}1) \\ &z_{2,3}^d(i,1) = q_1^u(i+1{,}1)((1 - R^d(i+1{,}1)) \end{aligned} \tag{13}$$

$$z_{3,1}^{d}(i,1) = (1 - r_{i+1})R^{d}(i+1,1)$$
$$z_{3,2}^{d}(i,1) = r_{i+1}(1 - R^{d}(i+1,1))$$
$$z_{1,2}^{u}(i+1,1) = 0$$
$$z_{1,3}^{u}(i+1,1) = 0$$
$$z_{2,1}^{u}(i+1,1) = q_{1}^{d}(i,1)R^{u}(i,1)$$
$$z_{2,3}^{u}(i+1,1) = (1 - R^{u}(i,1))q_{1}^{d}(i,1)$$
$$z_{2,1}^{u}(i+1,1) = q_{1}^{d}(i,1)R^{u}(i,1)$$
$$z_{3,1}^{u}(i+1,1) = R^{u}(i,1)(1 - r_{i+1})$$
$$u_{3,2}^{u}(i+1,1) = (1 - R^{u}(i,1))r_{i+1}$$

Interruption of flow

$$p_{1}^{d}(i,1) = p_{i+1} \tag{14}$$
$$p_{2}^{d}(i,1) = \frac{1}{W^{d}(i,1)}[X_{2}^{d}(i,1)(R^{d}(i+1,1) + q^{u}(i+1,1)(1 - R^{d}(i+1,1)))$$
$$-X_{3}^{d}(i,1)r_{i+1}(1 - R^{d}(i+1,1))]$$
$$p_{3}^{d}(i,1) = 0$$
$$p_{1}^{u}(i+1,1) = p_{i+1}$$
$$p_{2}^{u}(i+1,1) = \frac{1}{W^{u}(i+1,1)}[X_{2}^{d}(i+1,1)(R^{u}(i,1) + (1 - R^{u}(i,1))q^{d}(i,1))$$
$$-X_{2}^{d}(i+1,1)(R^{u}(i,1) + (1 - R^{u}(i,1))q^{d}(i,1) - X_{2}^{d}(i+1,1)(1 - R^{u}(i,1))r_{i+1}]$$
$$p_{3}^{u}(i+1,1) = 0$$

Idleness failure

$$q_{1}^{d}(i,1) = p_{i+1}\frac{W_{d}(i,2)}{W_{d}(i,2)+X_{2}(i,2)+P_{s}(i,2)} \tag{15}$$
$$q_{2}^{d}(i,1) = 0$$
$$q_{3}^{d}(i,1) = 0$$
$$q^{u}(i+1,1) = p_{i+1}\frac{W^{u}(i+1,2)}{W^{u}(i+1,2)+P_{b}(i+1,2)+X_{2}(i+1,2)}$$
$$q_{2}^{u}(i+1,1) = 0$$
$$q_{3}^{u}(i+1,1) = 0$$

V. ALGORITHM AND NUMERICAL BEHAVIOR

A solution method for the decomposition equations must be devised once they have been generated. The decomposition equations are solved using an approach presented in this part. Algorithms developed for single-part production lines were used in the development of the DDX algorithm. (Dallery, David, & Xie, 1988). New approach contains two iterative loops, unlike previous one. An inner loop goes down the line in a given part type depending on previous iterations, then back up the line in the reverse directions. Using the previous iteration's parameter values, the control loops iteration moves the line in the middle kinds of components.

Step 0: Initialization

Initialize upstream and downstream parameters

Initialize boundary conditions

While (Step C.1 criterion is not met) do Step 1 through Step J

Outer loop iteration

```
    While (Step C.2 criterion is not met) do Step 1.1 and Step 1.2
    Inner loop iteration
Step 1.1: Upstream Sweep for Type 1
    for i = 1 to NumMachines
            Evaluate Two Machine Line L(i-1; 1)
            Calculate $p_1^u(i,1)$,$p_1^u(i,1)$,$r_1^u(i,1)$,$r_2^u(i,1)$,$r_3^u(i,1)$,$z_{2,1}^u(i,1)$,
            $z_{2,3}^u(i,1)$,$z_{3,1}^u(i,1)$, and $z_{3,2}^u(i,1)$
            end
Step 1.2: Downstream Sweep for Type 1
    for i = NumMachines-1 to 1
            Evaluate Two Machine Line L(i + 1; 1)
            Calculate $p_1^d(i,1)$,$p_1^u(i,1)$,$r_1^d(i,1)$,$r_2^u(i,j)$,$r_3^u(i,1)$,$z_{2,1}^d(i,1)$,
            $z_{2,3}^u(i,1)$,$z_{3,1}^u(i,1)$,$z_{3,2}^u(i,1)$
            end
    end
for j=2 to NumParts-1
While (Step 5 criterion is not met) do Step j.1 and Step j.2
Step j.1: Upstream Sweep for Type j
    For i = 1 to NumMachines
            Evaluate Two Machine Line L(i-1; j)
            Calculate $p_1^d(i,j)$, $p_1^u(i,j)$,$r_1^u(i,j)$, $r_2^u(i,j)$,$r_3^u(i,j)$,
            $z_{2,1}^u(i,j)$,$z_{2,3}^u(i,j)$ ,$z_{3,2}^u(i,j)$, q(i,j-1)
    end
Step j.2: Downstream Sweep for Type j
    For i = NumMachines-1 to 1
            Evaluate Two Machine Line L(i+1; j)
            Calculate
            $p_1^d(i,j), p_1^u(i,j), r_1^d(i,j), r_2^u(i,j), r_3^u(i,j)$
            $z_{2,1}^d(i,j), z_{2,3}^u(i,j), z_{3,1}^u(i,j), z_{3,2}^u(i,j), q(i,j-1)$
```

end;

Step C.1: Evaluate Inner Loop Stopping Criterion

Terminate the inner loop when the maximum value of $\|E(i,j) - E(0,j)\|$

for i = 1,… NumMachines is less than some pre-specified ϵ for each

part type j.

Step C.2: Evaluate Outer Loop Stopping Criterion

Terminate the algorithm when the maximum value of $\left\|E^{(m-1)}(i,j) - E^{(m)}(i,j)\right\|$

where i = 1,… NumMachines and j=1,… NumParts and (m) is the outer loop

iteration repetition number, is less than some pre-specified δ.

The MTTF and MTTR of each machine in the line are about the same, and the MTTR is about an order of magnitude less than the MTTF. This includes the supply, processing, and demand machines. These values seem to be where the algorithm converges most often. The method is less likely to converge successfully if one machine's mean time to failure and mean time to repair are significantly different from another. What happens when two machines that are close to each other break down at separate times? It takes five to ten iterations for the inner loop to converge, according to this research, but it takes less than three for our loop to do the same.

Burman's testing procedure is used to verify the algorithm's reliability and accuracy since it is difficult to prove convergence mathematically (Burman, 1995). Algorithms are tested on a variety of randomly generated scenarios, where parameters of the random systems fall within pre-determined limits. Results from discrete-event simulations are compared to those from the algorithm.

A. Numerical Results for Two-Part-Type Lines

The algorithm was tested on production lines with five machines processing two different kinds of parts. The test creates a random set of 300 characters. The demand for Type 1 and Type 2 is approximately equal in the first 100 randomly selected lines. Part Type 1 demand is up to 30% higher in the second 100 occurrences than Type 2 demand. Part Type 2 demand is up to 30% higher than part Type 1 demand in the remaining 100 instances. From five to twenty buffers may be used.

Figures 5 and 6 show the computed percent errors for all 300 instances. Type 1 has an average absolute error of -0.52%, while Type 2 has an average absolute error of 2.2%. Type 1 and Type 2 buffer levels have average errors of 7.3% and 8.2%, respectively. The figures show that the algorithm underestimates the production rate of Type 1 parts while overestimating the production rate of Type 2 parts.

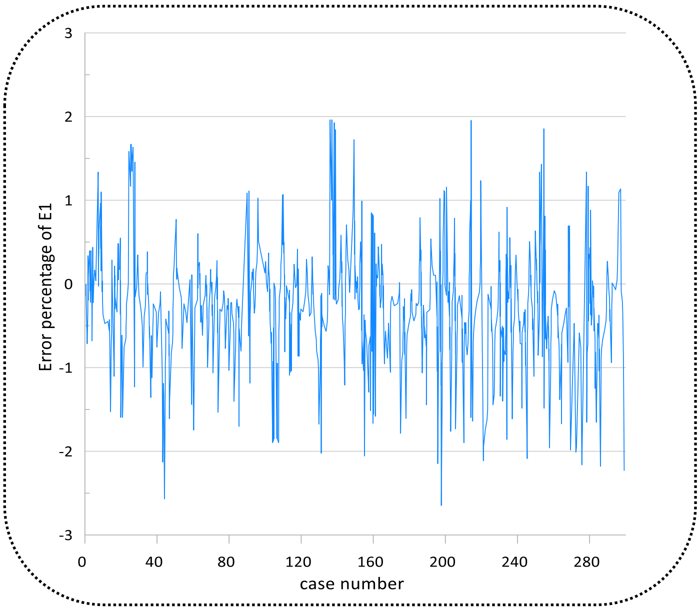

Fig 5. The errors in the decomposition approximation for type 1 production rates

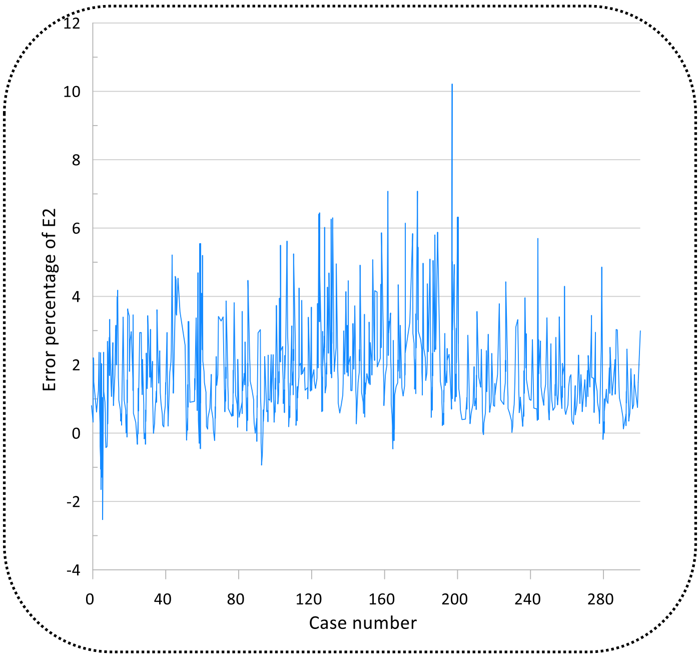

Fig 6. Type 2 production rate estimate inaccuracy in decomposition

B. Sensitivity Analysis

In order to get a better understanding of the system performance of the multiple-part-type line, a system sensitivity study was conducted on a line that processes three different types of components. The following manufacturing line is comprised of a single machine for processing, three machines for meeting demand, and three machines for meeting supply. Both machines and buffers have their limitations and might be unreliable at times. Even though there's just one operating equipment on the line, it's long enough to record the dynamics, with fascinating results. Even if there's just one processor on the line, it's wide enough to capture system dynamics.

Many factors may be assessed and their influence on system behavior can be studied in the discipline of sensitivity analysis. This includes demand, processing machine capacity, and buffer size. We are solely concerned with demand's influence on these variables. We begin by analyzing how the line responds to varying demand rates. Supply rates must be high enough to prevent frequent shortages in the processing equipment. We can better study the impact of fluctuating demand rates when we use high supply rates. Demand rates are more likely to fluctuate than supply rates if the processing machine is seen as a versatile production line that can handle a variety of products.

As an illustration, consider the following fictitious scenario: Line M1's machine symbolizes a manufacturing line processing three different sizes of sedans: a full-size sedan, a compact sedan, and an economy car. For a fraction of the total production expenses, the line may switch from one model to another using automated and flexible manufacturing. This line has a strict prioritization system in place. For the sake of this hypothetical classification, the luxury, full-size, and economical models are designated as Types 1, 2, and 3. Figure 7 illustrates how the demand for Type 1 changes over time. Table 2 shows the relevant system parameters.

Table II. Machine and buffer parameters for Figure 7

Machines		***Buffers***	
p0,1	0.93	b0,1	14
p0,2	0.93	b0,2	14
p0,3	0.93	b0,3	14
p1,1	Varying	b1,1	14
p1,2	0.55	b1,2	14
p1,3	0.55	b1,3	14
p1	0.846		

Supply machine (M_0;j) characteristics are selected such that each supply machine has a production rate of 0.93. The M_1 processing machine's isolated production rate is 0.846. Type 2 and Type 3 demand machines have isolated production rates of 0.55 and 0.55, respectively. Type 1 has a demand rate of 0.08 to 0.83. The buffer sizes are the same. Type 1 patients' heart rates are fluctuating.

According to Figure 7, a component type's throughput changes when the demand rate for type 1 rises or falls. Production for type 1 grows linearly at a roughly 45-degree angle as seen in the picture. In order to ensure that type 1 is always available to the processing machine, every effort is taken to meet its needs whenever possible. For type 1, the processing machine allocates a greater portion of its resources. Throughput rates for types 1 and 2 are decreasing as demand for type 1 increases. In order for the machines to properly process type 1, processing time is longer than processing time for types 2 and 3. Type 2 always outperforms type 3 in terms of throughput due to our priority rule.

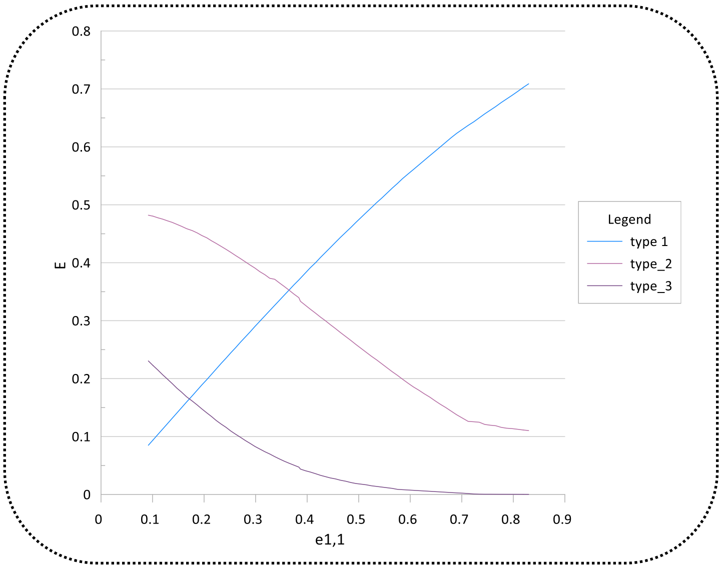

Fig 7. Throughput vs Demand for Type 1

VI. Conclusions

We provide in this paper a model and analytical study for a flexible production line, processing various parts types and unreliable equipment, and finite buffers. Static priority rules specify the order of priority for machines in a production line, with machines working on the most crucial parts as far as practical and on lower priority parts only when the more important components cannot be processed owing to blockage or hunger. We construct decomposition equations and a solution technique for line analysis. The approach converges with proper line parameters. Simulations validated decomposition results. Parameters exhibit interesting line properties.

The re-entrant flow line is also given decomposition formulae. For re-entrant systems, we change multi-part manufacturing line decomposition formulae. The results of the analytical model are compared to those of the simulation in the verification process. During the experiment, we saw that the analytical findings closely matched our initial assumptions and the simulation's outcomes. An optimum buffer algorithm for the multi-part allocation line may be built based on decomposition equations. The buffer size may be utilized to regulate product flow and plan for various commodities.

1. In the end, as suggestions and management solutions, it is recommended that companies create success in the field of flexible production structures in their organizational chart whose main task is to acquire up-to-date knowledge, research in areas relevant to production products, new production methods, and create solutions to operate new methods with available resources. Partnership with successful companies in the field of flexible production should be included in the company development program and successful examples in production systems should be properly modeled. Researchers who intend to continue this path are advised to conduct research activities in the field of modern methods of mathematical implementation and modeling of flexible production systems in different companies.

2. Achieving significant advances in the production of diverse and quality products has enabled leading companies in this field to be able to create a sense of pleasure and dominance in consumers of their products, and this is one of the most valuable keys to gaining a competitive advantage in today’s growing markets. To achieve this competitive advantage, successful companies will be able to identify customer needs faster than their competitors and produce and sell their products in the market sooner. Offering a variety of products tailored to customer needs increases the manufacturer's ability to retain its customers. Achieving flexible production methods and making them operational leads to the production of various products with the lowest cost and least changes in production lines and provides more production ability that results in maximum profit for the manufacturer and creates a sense of satisfaction in the customer to buy different products from other available products on the market. Fms is a simple way for industry owners to enable them to achieve agility. A solution that creates a sense of power in the manufacturer. The present study is an attempt to better understand the flexible production system and its mathematical modeling and present it to industry managers to use methods to remove barriers to these lines to make it easier to achieve new production systems.

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