# Prioritization and Efficient Route Selection in Automotive Parts Manufacturing

THESIS

DOCTOR OF PHILOSOPHY

in

MECHANICAL ENGINEERING

**By**

**Sumit Chawla**

**(2K17/Ph.D/ME/21)**

Supervisor

**Prof. Ranganath M. Singari**

DEPARTMENT OF MECHANICAL, PRODUCTION,
INDUSTRIAL & AUTOMOBILE ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

DELHI-110042 (INDIA)

**DELHI TECHNOLOGICAL UNIVERSITY**
Shahabad Daulatpur, Main Bawana Road
Delhi-110042 (India)

# CERTIFICATE

This is to certify that the thesis entitled "**Prioritization and Efficient Route Selection in Automotive Parts Manufacturing**" submitted by **Mr. Sumit Chawla** to **Delhi Technological University (Formerly DCE)**, for the award of the degree of "*Doctor of Philosophy*" in Mechanical engineering is a record of *bona fide* work carried out by him. Sumit Chawla has worked under my guidance and supervision and has fulfilled the requirements for the submission of this thesis, which to our knowledge has reached requisite standards.

**Prof. Ranganath M. Singari**
Head (Department of Design)
Professor
Department of Mechanical, Industrial,
Production and Automobile Engineering
Delhi Technological University (DTU)
Bawana, Delhi-110042

# ACKNOWLEDGEMENTS

First and foremost, I am thankful to almighty GOD for keeping me fit, healthy and energetic during entire course of my Ph.D. work.

I would like to express my gratitude to **Prof. Jai Prakash Saini**, Vice chancellor, Delhi Technological University, Delhi for providing this opportunity to carry out this work in this prestigious institute.

I would like to thank **Prof. Suresh Kumar Garg**, DRC Chairman and Head of the department Mechanical engineering, for their support to finish this work.

With pleasure, I would like to express my greatest gratitude to my supervisor **Prof. Ranganath M. Singari**, Head of the department of Design and Professor, Department of Mechanical Engineering, Delhi Technological University for their proficient guidance, intelligent approach, constructive critique, wholehearted and ever available help, which has been the primary impetus behind the research. Without the wise advice and able guidance, it would have been impossible to complete the thesis in this manner.

I wish to record my thanks and gratitude to our all Internal and External SRC experts, **Prof. P M Pandey** (Director, BIET Jhansi ), **Prof. Abid Haleem** (Jamia Millia Islamia), **Prof. R.S Mishra**, **Prof. Reeta Wattal** and **Prof. Rajan Yadav** for their valuable guidance, critical and constructive discussion during this work.

I also convey my sincere thanks to my seniors Dr. Anurag Sharma, Dr. Shadab Ahmad, Dr. Ramakant Rana, and Mr. Mohd Tayyab for their patience and active support. Thanks are due to the wonderful friends in my life who were always on the standby to bring me to *positivity, hope and smiles when things didn't seem favouring, and it seemed a far-fetched journey.*

*I am greatly indebted to my parents and my wife for their love and blessings to see me scaling greater heights of life.*

*Above all, I would thanks Almighty for blessing such an affectionate & efficient people playing great asset for me.*

**(*Sumit Chawla*)**

# TABLE OF CONTENTS

# LIST OF FIGURES

# LIST OF TABLES

# LIST OF ABBREVIATIONS

| | |
|---|---|
| AHP | Analytical hierarchy process |
| AI | Artificial Intelligence |
| ANN | Artificial neural network |
| ANOVA | Analysis of variance |
| ANP | Analytic network process |
| ARAS | Additive ratio assessment |
| ATC | Apparent tardiness cost |
| AWINQ | Anticipated work in next queue |
| BM | Buffing machine |
| CF | CNC fettling |
| CNC | Computer numeric control |
| COPRAS | Complex proportional assessment |
| COVERT | Cost over time |
| CR | Critical ratio |
| DCM | Die casting machine |
| DEA | Data envelopment analysis |
| DEMATEL | Decision making trial and evaluation laboratory model |
| DM | Drilling machine |
| DSSs | Decision support systems |
| EAS | Energy aware scheduling |
| EDD | Earliest due date |
| EESP | Energy-efficient scheduling problems |
| ELECTRE | Elimination et choice translating reality |
| ELSP | Economic lot scheduling problem |
| ERD | Earliest release date |
| ERP | Enterprise resource planning |
| EV | Electric vehicle |
| FCFS | First come first serve |
| FFS | Flexible flow-shop scheduling |
| FIS | Fuzzy inference system |
| FLS | Fuzzy logic system |
| FMEA | Failure mode and effects analysis |

| | |
|---|---|
| FMS | Flexible manufacturing system |
| FOFO | First off first on |
| GA | Genetic algorithm |
| HFS | Hybrid flow shop |
| HMOGWO | Hybrid multi-objective grey wolf optimizer |
| HSA | Hybrid Simulated Annealing |
| HVAC | Heating, ventilation, and air conditioning systems |
| IEEE | Institute of electrical and electronics engineers |
| JSSP | Job-shop scheduling problems |
| LPT | Longest processing time |
| LRP | Least remaining processing time |
| LRP/OP | Least average remaining processing time |
| LWKR | Least work remaining |
| MADM | Multi attribute decision making |
| MATLAB | Matrix laboratory |
| MCDM | Multi criteria decision making |
| MDD | Modified due date |
| MF | Manual fettling |
| MHS | Material handling systems |
| MOD | Modified operation due date |
| MODWSP | Multi-objective dynamic welding scheduling problem |
| MOORA | Multi-objective optimization method by ratio analysis |
| MOR | Most remaining number of operations |
| MRP | Material requirements planning |
| MRP | Most remaining processing time |
| MRP/OP | Most average remaining processing time |
| MST | Minimum slack time |
| NINQ | Number in next queue |
| OCRA | Operational competitiveness rating analysis |
| ODD | Operation due date |
| PDC | Pressure die casting |
| PROMETHEE | Preference ranking organization method for enrichment evaluation |
| PS | Painting shop |

| | |
|---|---|
| QA | Quality assurance |
| RFID | Radio-frequency identification |
| SAF | Self-adjusted fuzzy |
| SCADA | Supervisory control and data acquisition |
| SDST | Sequence dependent set up time |
| SIO | Shortest imminent operation time |
| SNQ | Smallest number in queue |
| SPM | Special purpose machine |
| SPT | Shortest processing time |
| SRW | Shortest remaining work |
| SST | Shortest setup time |
| STR | Slack Time Remaining |
| TEC | Total energy consumption |
| TIG | Tungsten inert gas |
| TOPSIS | Technique for order preference by similarity to ideal solution |
| TPT | Total processing time |
| TSPT | Truncated shortest processing time |
| TTT | Total travel time |
| TWIQ | Total work in queue |
| UTA | Utility additive |
| VIKOR | Vlse Kriterijumska Optimizacija Kompromisno Resenje |
| VMC | Vertical milling center |
| WEED | Weighted earliest due date |
| WINQ | Least work in queue |
| WSPT | Weighted shortest processing time |

# Abstract

Scheduling automotive part manufacturing is a more arduous and complex task. It is a very backbreaker task to get an optimum schedule for any automotive part manufacturing. In today's scenario, every industry and research organization need an energy-efficient system to cope up with the global environment. In this study, a first-time energy-efficient fuzzy scheduling system is developed for crankcase cover manufacturing under uncertain processing times. This study consists of the development of an energy-efficient fuzzy inference system of the four-crankcase cover (cover left side crankcase KWPG, cover left crankcase K38, cover crankcase 206 G, and cover right crankcase KTE) and its results are validated by the fuzzy set approach. Fuzzy logic provides a decision by a combination of the rules for selecting job priorities and route selection. This scheduling system also provides the trade-off between energy consumption and makespan. This study also deals with the identification of the best material for crankcase cover manufacturing. To satisfy customer needs, designers must predict the performance of all available materials and find out the best material for the product. Since the various materials are available in the market with diverse characteristics, which makes the material selection process is complex. So, there is an indispensable need for a proper material selection methodology. The designers must identify the best approach which enhanced the product performance and reduced the time of designing. In this study, the first-time selection of materials for a two-wheeler crankcase cover is done using integrated TOPSIS PROMETHEE, and MOORA model. The final rankings of alternatives obtained from this novel proposed model are also compared with each other for finding the best material for crankcase cover.

The research also focuses on the multi-objective single-machine static scheduling problems of motorcycle crankcase cover. To solve these single-machine static scheduling problems, dispatching rules are used. Various dispatching rules used in this study are EDD, SPT, CR, LPT, WSPT, COVERT, and Hodgson's algorithm. This study helps us to obtain optimal job prioritization of two-wheeler crankcase covers in the automobile industry. Results show that shifting the production system from WSPT approach scheduling to the EDD scheduling approach; minimizes the mean flow time, weighted mean flow time, and maximum lateness.

The Automotive industry is one of the biggest emerging sectors in terms of revenue. Every automotive industry has an indispensable need for optimum manufacturing scheduling systems for generating good revenues and profits. This need can be pulled off by

identifying and prioritizing the scheduling parameters also. MCDM is one of the best techniques of operation research in selecting the best parameters or factors among the various alternatives. This study includes the identification and prioritization of the various important scheduling parameters in the Indian automotive industry. The twelve scheduling parameters have been identified in this study and these parameters are prioritized by the fuzzy-TOPSIS and DEMATEL model. These methods best deal with uncertainty and vagueness. The first time, fuzzy TOPSIS and DEMATEL are applied in prioritizing the SPs in the automobile industry. The expert's views are gathered from the five automobile industries. Makespan, energy consumption, due date, and travel time are the crucial parameters obtained using fuzzy TOPSIS. The least important parameters obtained using fuzzy TOPSIS are work in process, flow time, and release date. The most influential parameters identified using the DEMATEL method are completion time and processing time. This study is very useful for all automotive industries as well as research organizations. This study also deals with the development of a simulation model of crankcase cover manufacturing.

The simulation creates the virtual production model which is exactly like the real environment, and it provides future insights before laying down the actual production plant layout. With the help of simulation, we can simulate the complex and costly manufacturing system without being investing money physically and check the system's real-life behavior. In this study, the modelling and simulation of two-wheeler crankcase cover manufacturing are done with the help of flexsim. This study deals with the development of a simulation model for crankcase cover manufacturing systems in the automobile industry. Flexsim simulation tool is used as an optimization tool for identifying the bottleneck present in the production line to improve the system performance and line efficiency. The results indicate that by eliminating the bottleneck in the production line, it increases the line efficiency as well as the production throughput. These results are useful for all industries for simulating their process or product layout.

# Chapter-1

# INTRODUCTION

The motorcycle as a product proves to be particularly complex during the design and production stages. The components of a motorcycle are comprised of several thousand pieces. Motorcycle customers can only have a good impression of the product once it has been physically seen and tried out. The distribution logistics of this product are very complex as well [204].

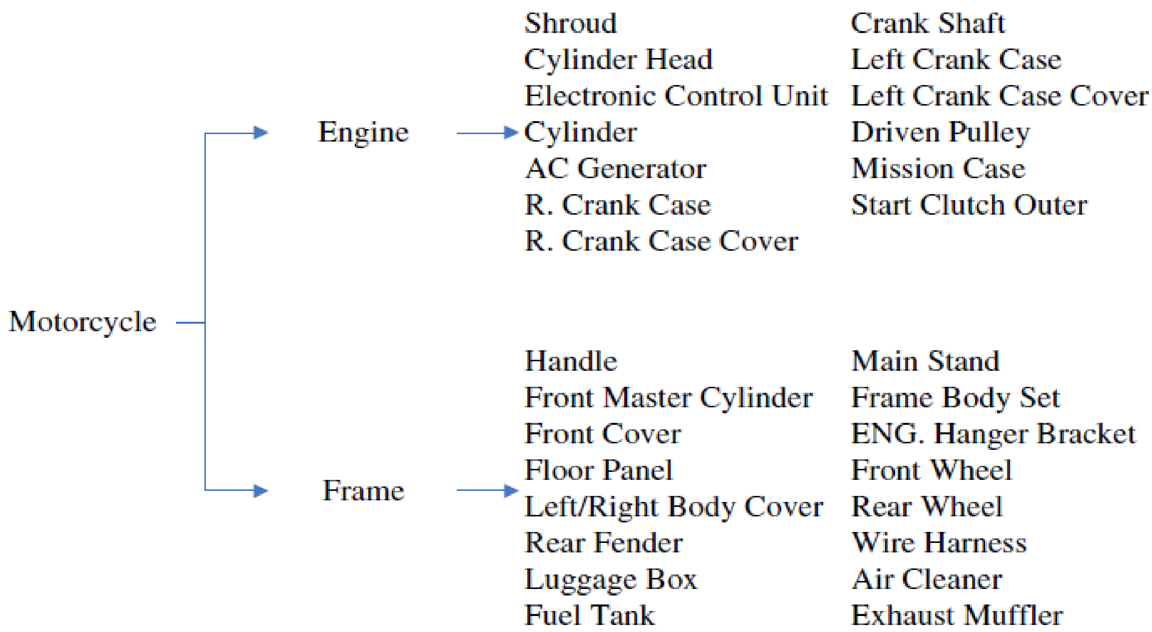


Fig.1.1 Motorcycle component network [204]

## 1.1 Automotive Part Manufacturing

Automotive part manufacturers are manufactures of pressure die casting and sheet metal parts, sub-assemblies, and assemblies related to automobiles, engineering, construction decorative, electrical accessories, and machine tools.

These manufacturers are equipped with a wide range of machines from 120 Tons to 800 Tons with the auto ladle, auto spray, and auto extractor along with other peripheral equipment for other operations, such as painting, shot blasting, heat treatment, and impregnation. They have set up one of the most modern CNC machine shops to supply fully finished ready to use components.

The Sheet Metal division has facilities of mechanical & hydraulic presses ranging from 10 Tons to 250 Tons, shearing machines, welding machines, CNC pipe bending, and paint shop. In-house tool designing and manufacturing, tool room, and QA are the major strengths supporting the sheet metal plant.

Fig. 1.2 Some automobile components (Super Auto India limited, 2022)

### 1.2 Fuzzy Logic

The concept of fuzzy logic was developed by Lotfi Zadeh in 1965. Lotfi Zadeh presented this approach, not as a control methodology. This approach can process data by providing only a partial set of membership i.e., incomplete, and uncertain information rather than crisp membership or non-membership. This approach is not used or applied as a control methodology till 1960 due to insufficient small capacity computers. Professor Zadeh told that people do not require exact, precise, certain, or numerical type input. Without this type of input also, they are capable of highly adaptive control. The structure of the fuzzy logic system consists of mainly four functional blocks i.e., rule base, fuzzifier, defuzzifier, and inference. The structure of the fuzzy logic system is shown in Fig. 1.3.

The function of each block is as follows:

- Rule base: It consists of several If-THEN fuzzy rules. The most important part of fuzzy is the knowledge base which combines the rule base and database. The database defines the membership functions of the fuzzy sets used in the fuzzy logic system.

- Fuzzifier: It is used to apply real input or exact input also called crisp input to the fuzzy system. This crisp input contains precise information about the specific information of a particular parameter. It transforms the crisp inputs into linguistic variables of fuzzy i.e., it converts the precise quantity to the form of imprecise quantity like 'small', 'medium', 'high' etc. with some degree of membership to it.
- Inference: It is a decision-making unit that performs the inference operations on the rules. Output generated by inference is generally fuzzy.
- Defuzzifier: It transforms the linguistic variables of fuzzy into crisp output or real-world output. Output generated by inference is taken as input for the defuzzifier.

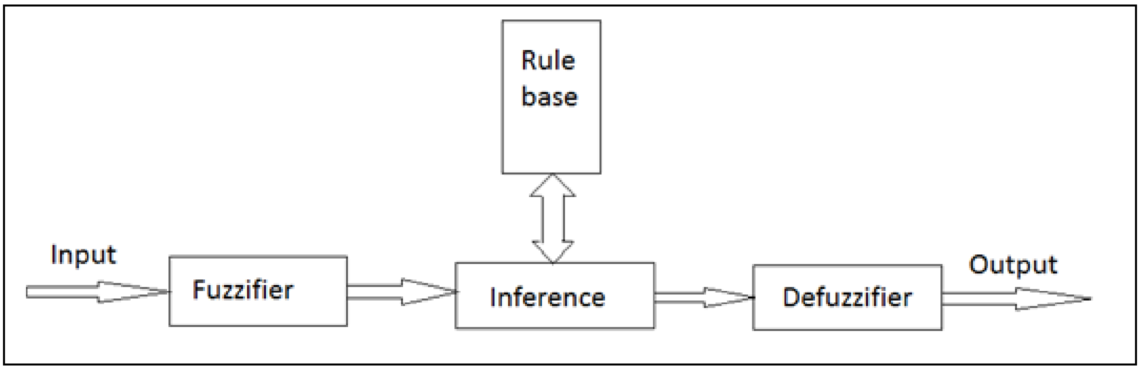


Fig.1.3 Structure of Fuzzy logic system

### 1.3 Material Selection of Crankcase Covers

Proper material selection leads to improved product quality, cost, and productivity. Proper material selection is not based on single criteria or dimensions. The designers need to consider multiple criteria for material selection [225]. The goal of every designer is to select the best material for optimal design to reduce cost and enhance performance [237]. The accuracy of the material selection depends on designer experiences and the material data record used [86]. Improper selection leads to failure in customer satisfaction and incurs huge losses for the industry also. The designers must have detailed knowledge of all criteria or attributes for product development and design [146]. Initially, before the material selection, material screening is done with the help of the chart method, knowledge-based system method, or the computer-aided method [75].

The Material selection for crankcase cover is a complex and challenging engineering problem because of the large no. of alternatives with diverse properties [227]. A two-wheeler crankcase cover is generally manufactured by the cold chamber die casting process. Aluminum alloys have a very good performance-to-weight ratio and are easy to cast. Aluminum alloys are the first choice for all the products manufactured by the die casting techniques because these alloys provide superior performance to weight ratio and low specific gravity value. Aluminum alloys are mainly alloyed with silicon, magnesium, copper, iron, manganese, and zinc to enhance their properties. Eleven aluminum alloys are worldwide used in various die casting processes. Out of these eleven alloys, some aluminum alloys are difficult to cast e.g., Alloy A 360, Alloy 43, and Alloy 218. Alloy 390 has the least machining characteristics because of the presence of high silicon in it. Six aluminum alloys are taken as alternatives for crankcase cover materials and seven attributes (brinell hardness, yield strength, % elongation, young’s modulus, ultimate tensile strength, fatigue strength, and material cost) is taken as criteria. The % elongation property represents the ductility or crash resistance of the material. This property is considered as beneficial criteria because more % elongation provides more safety to the passengers by dissipating some failure effects into plastic deformation. The young’s modulus is a material property representing the stiffness of a material. This property remains constant for isotropic material and varies for an anisotropic material. To get a more reliable result of material selection, most of the researchers have used more than one MCDM approach [133, 182, 202, 206, 273]. Many researchers have used the TOPSIS and MOORA methodology in various material selection problems as discussed in the literature part. Integrated TOPSIS MOORA methodology can be used for the new product selection [56]. The first time, both these approaches are applied simultaneously for material selection of crankcase cover in the automobile industry.

**1.4 Stratification of Scheduling Problems**

Production Scheduling is a very important decision-making process that includes the proper allocation of all the available resources for performing all tasks [7]. On-time delivery of products or services provides customer satisfaction and scheduling helps in achieving on-time delivery [223]. The primary objective of scheduling includes determining the job processing time, due date, and sequence of jobs [252].

Scheduling problems can be stratified into two types: [28]

1. Static scheduling problems
2. Dynamic scheduling problems

Static scheduling problems consist of a fixed no. of jobs that are to be completed and it uses criteria called minimum makespan. Deterministic and stochastic types of solutions are used in both static and dynamic types of approaches. Deterministic solutions use known and fixed process time. These solutions use methods like methods producing optimum results (used for small problems) and methods using the heuristic procedure (based on dispatching or sequencing rule). Stochastic solutions use variable process time. Fig.1.4 shows the Stratification of scheduling problems.

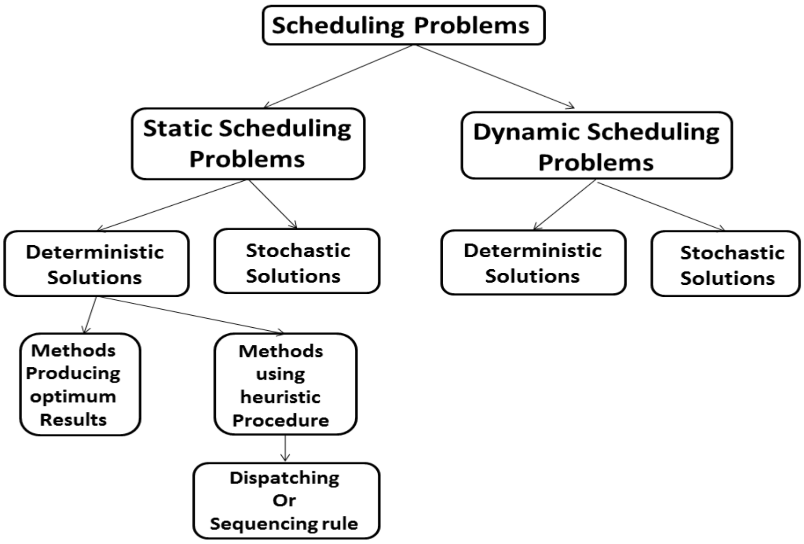


Fig. 1.4 Stratification of scheduling problems

Methods using heuristic procedures are based on the common priority sequencing rule. These rules can be classified into single and multi-dimension rules. Single dimension rules consist of SPT, EDD, and FCFS. The due date can be calculated with computerized methods like MRP, or it can be determined from the customer directly. Multi-dimension rules consist of critical ratio and slack per remaining operations. Fig. 1.5 shows the classification of the sequencing rule.

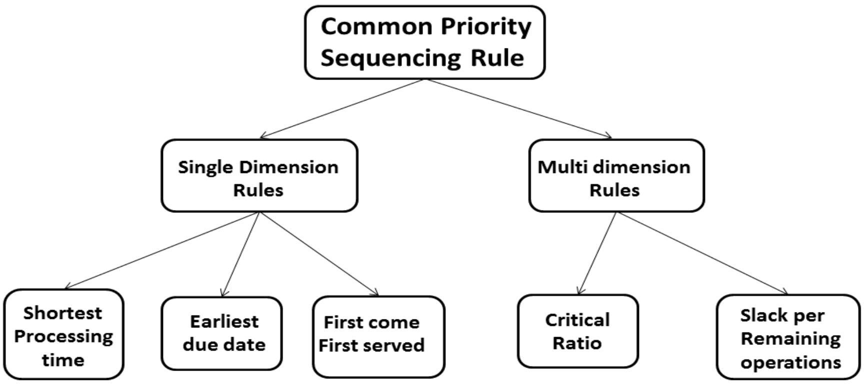


Fig. 1.5 Classification of sequencing rules

These dispatching or sequencing rules can also be classified based on priority determination of each job, dynamics of the information base, or maybe based on machine and job selection.

Dispatching rules can be stratified into local and global rules as shown in Fig. 1.6. Local rules used only limited available information, but global rules used all information present on the shop floor.

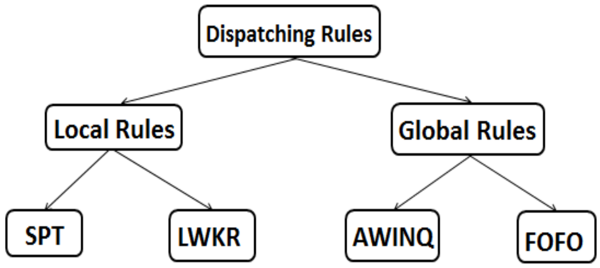


Fig. 1.6 Sequencing rules based on the job priority determination

Dispatching rules can be classified into static and dynamic rules as shown in Fig. 1.7. Static rules do not depend on time, but they depend on the machine or job data e.g., earliest due date, earliest release date, and weighted shortest processing time rule. The dynamic rule is time-dependent e.g., shortest processing time and modified due date etc.

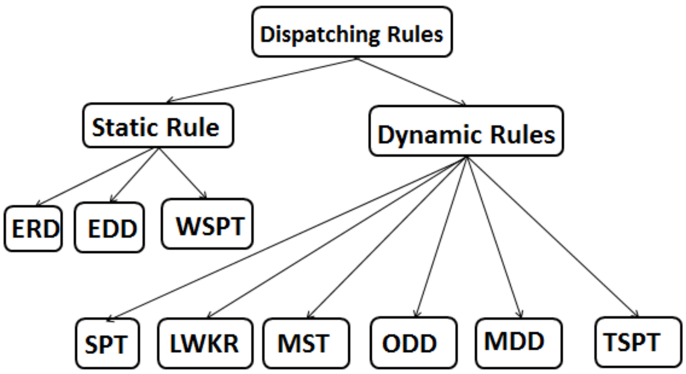


Fig. 1.7 Sequencing rules based on dynamics of the information base

The MDD rule is a combination of EDD and SRPT which is effective in minimizing mean tardiness [139]. Dispatching rules can also be stratified based on job and machine selection as shown in Fig. 1.8. Dispatching rules based on job selection are SPT, EDD, etc. Utilization is lowest, number in next queue, modified due date, and TSPT are some rules based on machine selection [186].

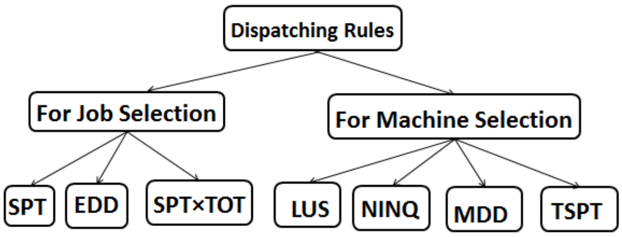


Fig. 1.8 Sequencing rules based on machine or job selection

The dispatching rule gives good results only in the case of a single objective but in real problems, combinations of objectives are present which is tackled by a combination of dispatching rules. These combinations of dispatching rules are called Composite dispatching rules [223]. Q. Zhou et al. analysed the dynamic priority scheduling problem of data dissemination systems [303]. Real-life applications of Scheduling include manufacturing scheduling, scheduling in a service industry, scheduling in a computer system [223], automotive product-process innovations [105], and process integration and innovations [243].

### 1.5 Manufacturing process of crankcase cover


Fig. 1.9 General process sequence for crankcase covers manufacturing

Generally, 60% fresh aluminum brick and 40% rejected pieces are used for melting in a furnace. Each aluminum brick (raw material) is 5 kg. A ladle is used to carry out the molten aluminum from the furnace to the PDC machine as shown in Fig. 1.10 and Fig. 1.11. Fig. 1.9 shows the general process sequence for crankcase covers manufacturing.

Fig. 1.10 Ladle carrying molten aluminum

Fig. 1.11 Pressure die casting machine

Fig. 1.12 Crankcase covers obtained through PDC machine

Crankcase covers obtained through the PDC machine are shown in Fig. 1.12. Generally, the production rate of this crankcase covers is 50 parts per hour. But it varies according to the variation in the parts. The target production per hour for cover Lk 38 is 60.

CNC usually vertical milling center is used for machining of these crankcase covers after fettling and drilling operation (as shown in Fig. 1.13). The cycle time of cover LK 38 is 5 min 24 seconds which includes a cutting time of 3 min 28 seconds and a non-cutting time of 1 min 28 seconds. The cutting time to cycle time ratio for cover LK 38 is 84%.

Fig. 1.13 Machining operations on VMC

After machining and buffing operation, pre-treatment or surface treatment processes are done which include some operations as given below.

1. Degreasing
2. Water Rinse-I
3. Water Rinse –II
4. Water Rinse –III
5. Nano processes
6. Water Rinse IV

This pre-treatment process is done almost for 12 to 15 min for removing surface defects. Almost 150 crankcase covers can be pre-treated simultaneously in one lot. The pre-treatment operations details are given in Table 1.1.

Table 1.1 Pre-treatment operations

| Pretreatment Operation | Medium Used | Dip time | ph value |
|---|---|---|---|
| Degreasing | Raw Water | 5 min | - |
| Water Rinse-I | Raw Water | 1 min | 7-9 |
| Water Rinse –II | Raw Water | 1 min | 7-8 |
| Water Rinse –III | DM water | 1 min | 6.5-7.5 |
| Nano processes | - | 3 min | 3-4.5 |
| Water Rinse IV | DM water | 1 min | 5-7.2 |

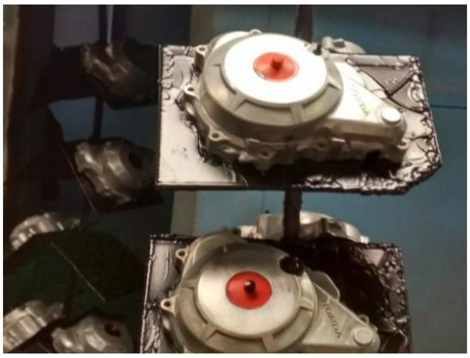

Fig. 1.14 Masking operation

After the pre-treatment process, the masking operation is done for covering those parts where there is no need for paint like in the threads of the crankcase covers. This operation is done before the painting operation. Fig. 1.14 shows the masking operation. The second last stage of crankcase covers manufacturing is the painting shop. The product remains in the painting shop for almost 2 hours. The painting stage includes loading, primer, base coat, top coat, Honda monogram PU red paint, and baking in the oven. Baking time is 10 min and baking temperature is 90 degrees. The last stage is the inspection and packaging.

### 1.6 Energy Consumption scenarios in the various industries

The energy consumption in the industrial sector is increasing tremendously every year. Since, last 50 years, the demand for energy consumption in this sector becomes doubled, and nowadays, only the industrial sector is consuming almost the world's half energy. So, energy-efficient manufacturing is the need of every organization and industry [203].

Nowadays, every organization is facing a problem that how to convert their manufacturing system into an energy-efficient manufacturing system so that they can reduce energy consumption and can have the least adverse effect on the environment. Most of the researchers have used a static scheduling model in production scheduling problems for reducing energy consumption [251].

Today's research is based on decreasing the energy consumption of producing processes on the device level and the product stage by using the optimum schedule [145, 201]. Because of global warming and higher energy cost, efficient manufacturing is the need of every manufacturing as well as a research organization. Efficient machining and a machine tool are needed for reducing energy consumption within organizations [34, 120]. Almost 37% of the world's total energy is consumed by an industrial sector such as construction, machining, mining, and agriculture. The energy-saving techniques, policies, or several ways are discussed by E. A. Abdelaziz et al. in their research work [3].

This study is done for developing an energy-efficient fuzzy-based scheduling system for crankcase cover manufacturing. Many researchers have used the fuzzy methodology in various scheduling problems as discussed in the literature part. The first time, fuzzy approaches are applied for job prioritization and route selection of crankcase cover in the automobile industry.

### 1.7 Modelling and simulation of crankcase cover manufacturing

Simulation helps in the analysis of the various manufacturing system. It solved the problems related to resource allocation, scheduling, shop floor, material handling, storage, and manufacturing. Nowadays the different company provides different simulation software. This software reduces the production cost and provides effective resource allocation [33].

The various simulation software available in the market are Flexsim, Arena, Simul8, Anylogic, Witness, and Promodel. Flexsim is discrete event simulation software used for complex optimization problems. Flexsim is a very powerful tool used for modelling and simulation. This tool can be effectively used for appointment booking analysis and manufacturing problems. It also helps the management in hiring employees for future projects and changing the work schedules. The simulation also highlights any inefficiency or bottleneck occurring in the system [160].

The simulation approach can be effectively used in the design, production planning, and scheduling problems. These approaches help in decision-making problems and in finding more realistic results based on the actual dynamic conditions [96]. Flexsim consists of the experimenter tab of the design of experiments used for optimizing the set of solutions and performance of the production plant [137]. Flexsim tool can solve the multi-objective optimization problems and developed the hybrid simulation model which optimizes the various parameters such as makespan, due date, tardiness, work in process inventory and machine utilization, etc [232]. This tool provides a complete output report which can be analysed for measuring the performance of the system [210].

## 1.8 Objectives of the Thesis

The key objectives of the thesis are given below.

- To find out the best material for automotive part manufacturing.
- To develop energy efficient scheduling system for automotive part manufacturing and to find out the best feasible routes of machining these parts.
- To identify and prioritize the scheduling parameters in the automotive industry.
- Prioritize the automotive parts for production operations using various dispatching rules and to minimize the scheduling parameters such mean flow time, weighted mean flow time and maximum lateness etc.
- To develop a simulation model for automotive part manufacturing.

## 1.9 Outline of the Thesis

This thesis is organized into several chapters.

Current chapter 1 introduces the thesis and emphasizes the need of conducting this research. This chapter also identifies the aim and objective of the study.

Chapter 2 describes the literature review and past studies of various articles related to energy-efficient scheduling, fuzzy logic, material selection and dispatching rules, etc. It first represents the distribution of literature across various journals and then the literature review has been classified into various sub-sections. These sub-sections include literature based on scheduling, literature based on fuzzy logic, literature based on scheduling using fuzzy logic approach, literature review based on material selection, literature review based on the various dispatching rules, literature review based on the energy consumption scenario, literature review based on the MCDM approaches, and literature review based on the different approaches.

Chapter 3 explains the research methodology used in this thesis. Chapter 4 to chapter 8 formulates and explains the various case studies. Chapter 9 describes the results and discussions. Finally, the last chapter concludes the results with the future scope.

# Chapter-2

# LITERATURE REVIEW

Many researchers employed AI techniques to solve various manufacturing problems. A literature review is carried out on various published papers around the globe related to energy-efficient scheduling and production scheduling with metaheuristic approaches. Major prior works have been captured to identify the research gap.

For literature review papers from various international and reputed journals have been collected through the science directory, emerald, Sage, Springer, Taylor & Francis, Google scholar, and IEEE Explore from 1986 to 2022. During the review process, we targeted six main library databases that cover most of the scheduling applications, namely: Science Direct, Springer, Taylor & Francis, Emerald, IEEE, and Google scholar.

We tried to collect as many papers as possible that were feasible for us. From these 305 were separated, those were concerned with energy-efficient scheduling, production scheduling, Fuzzy logic their implementation, and related issues. The complete data have been tabulated as under regarding the distribution of papers across various journals in Table 2.1.

We focused on papers published over the last decade (starting from 2004). Due to the high number of papers published every year, we applied the following rule: "the more recent the year, the higher the number of papers reviewed", to guarantee relevant and up-to-date findings/remarks about energy-efficient scheduling. Fig. 2.1 gives valuable information regarding the number of papers reviewed per journal and Fig. 2.2 shows the number of papers, over the years that are reviewed and discussed in this study.

We have classified the literature review into eight sub-sections. These sub-sections include literature based on scheduling, literature based on fuzzy logic, literature based on scheduling using fuzzy logic approach, literature review based on material selection, literature review based on the various dispatching rules, literature review based on the energy consumption scenario, literature review based on the MCDM approaches, and literature review based on the different approaches.

## 2.1 Literature review based on Scheduling

Whenever restricted resources must be assigned to task elements for accomplishing these tasks over time, scheduling problems arise. Scheduling is relevant in different disciplines such as project management [103], aerospace industry [100], computer science [196], and personnel management [216]. Among the most prominent and important research fields in scheduling are production systems [224], which is also the focus of this study.

Table 2.1 Distribution of reviewed articles in various journals

| Name of Journal | No. of papers | Percentage |
|---|---|---|
| International Journal of Production Research | 26 | 12.94 |
| Journal of Cleaner Production | 14 | 6.97 |
| Computers & Industrial Engineering | 11 | 5.47 |
| European Journal of Operational Research | 8 | 3.98 |
| Appl. Math. Model | 7 | 3.48 |
| Applied Soft Computing | 6 | 2.99 |
| Applied Soft Computing | 6 | 2.99 |
| Engineering Applications of Artificial Intelligence | 6 | 2.99 |
| Procedia CIRP | 5 | 2.49 |
| Expert System with Applications | 4 | 1.99 |
| International Journal of Advanced Manufacturing Technology | 4 | 1.99 |
| International Journal of Production Economics | 4 | 1.99 |
| Journal of Quality in Maintenance Engineering | 4 | 1.99 |
| Computer & Operation Research | 3 | 1.49 |
| Journal of Intelligent Manufacturing | 3 | 1.49 |
| International Journal of Quality & Reliability Management | 3 | 1.49 |
| Computers & Chemical Engineering | 2 | 1.00 |
| Computers & Operations Research | 2 | 1.00 |
| International Journal of Computer Integrated Manufacturing | 2 | 1.00 |
| Journal of Scheduling | 2 | 1.00 |
| Journal of Manufacturing Systems | 2 | 1.00 |
| Renewable and Sustainable Energy Reviews | 2 | 1.00 |
| Fuzzy Sets Syst. | 2 | 1.00 |
| CIRP J. Manuf. Sci. Technol | 1 | 0.50 |
| Engineering Optimization | 1 | 0.50 |
| Fuzziness and Soft Computing | 1 | 0.50 |
| Information Systems | 1 | 0.50 |
| International Journal of Iron and Steel Research | 1 | 0.50 |
| International Journal of Productivity and Performance Management | 1 | 0.50 |
| J. Ind. Eng. Manage. | 1 | 0.50 |
| Journal of Advances in Management Research | 1 | 0.50 |
| Journal of the Chinese Institute of Industrial Engineers | 1 | 0.50 |
| Procedia Computer Science | 1 | 0.50 |
| Intelligent Automation and Soft Computing | 1 | 0.50 |
| Int J Syst Sci | 1 | 0.50 |

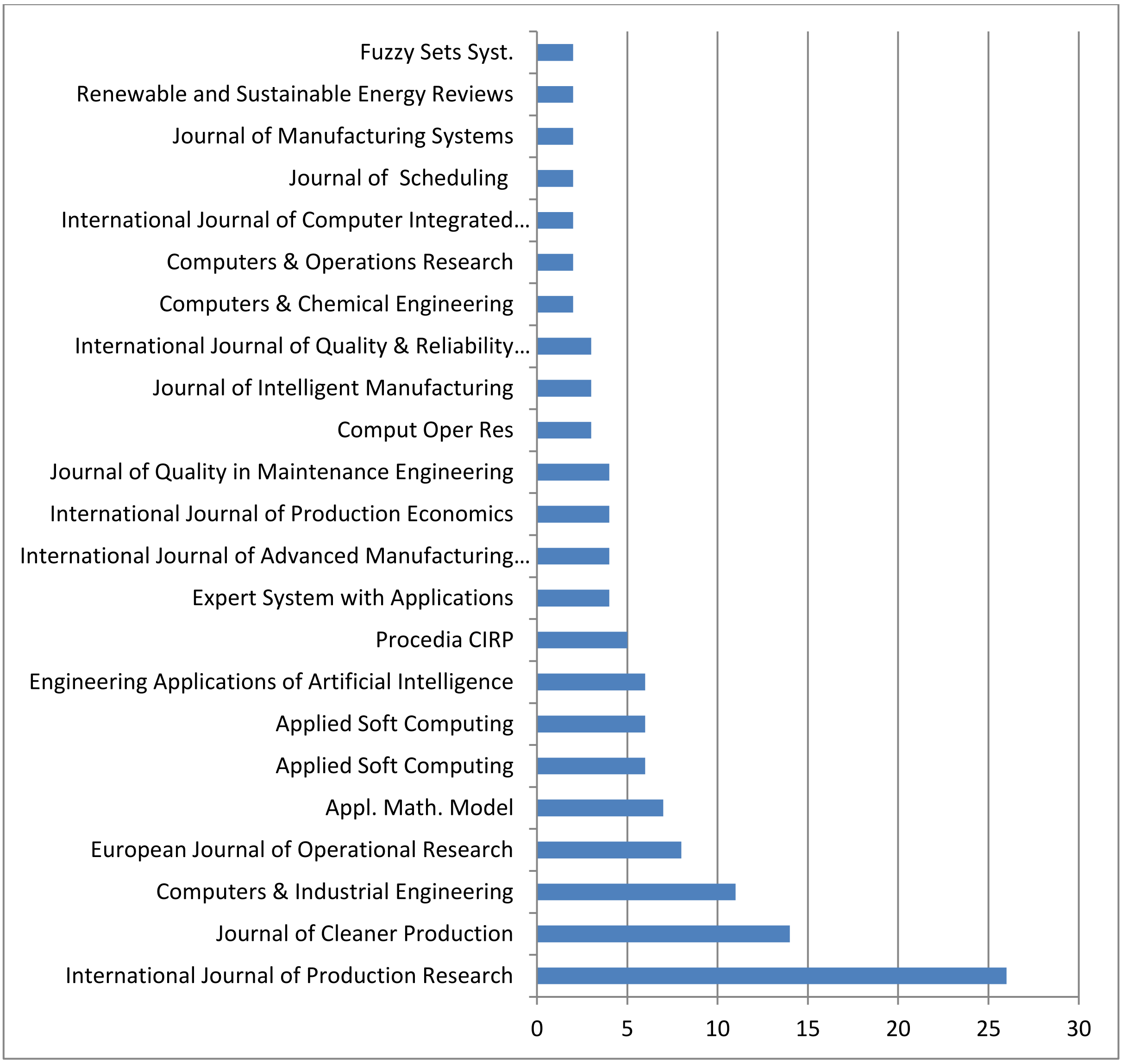


Fig. 2.1 No. of papers reviewed per journal

Pellegrinelli, S. et al. introduces a research activity dealing with the integration of energy consumption strategies in the design of work plans and distributed part programs and it also minimized the energy consumption during both the configuration of the pallet and the selection of alternative work plan [218]. Andrea Trianni et al. dealt with energy efficiency barriers with few empirical studies and thus promoting the most effective policies to secure widespread adoption of energy-efficient technologies and practices [259]. Fadi Shrouf et al. provide a mathematical model to minimize the total energy consumption costs for single-machine scheduling, considering the continuous changes in energy prices [239].

To thoroughly comprehend the steelmaking continuous casting Scheduling problems in the dynamic production environment, the concept of production scenario and its mathematical description was proposed, and the dynamic characteristics of the steelmaking continuous process were described.

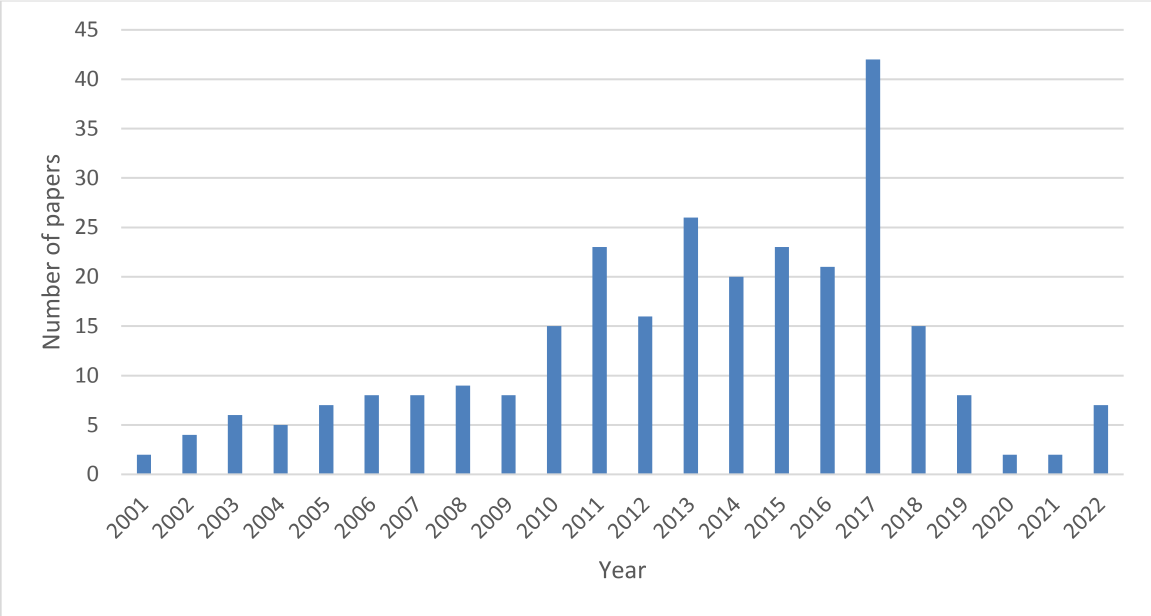

Fig. 2.2 No. of papers reviewed per year

Kostas S. et al. proposed a knowledge-based system for production scheduling using an ERP system. This system uses the prevailing conditions in the environment to choose the most appropriate dynamic scheduling algorithm [194]. Ann Tighe et al. described the successful use of self-organizing fuzzy control in enhancing dynamic optimization, a controller is used to direct the type of optimization appropriate in each new dynamic problem. The system uses its experiences to determine which approach is most suitable under varying circumstances [256]. Shiu Hong Choi and Feng Yu Yang studied the special topological structure of the disjunctive graph and proposed quick value-setting algorithms for solving the linear programming problems commonly encountered in job-shop scheduling [66].

S.A. Oke and O.E. Charles-Owaba revisited the literature of preventive maintenance scheduling, and they solved the problem of the simultaneous scheduling of resource-constrained preventive maintenance and operations. A case study from the shipping industry was used in their study [212]. Asif Raza and Mustafa Al-Turki compared the effectiveness of two meta-heuristics in solving the problem of scheduling maintenance operations and job processing on a single machine. Tabu search and simulated annealing are two meta-heuristic algorithms that were hybridized using the properties of an optimal schedule identified in the literature [229].

Subbaiah et al. solved scheduling problems in FMS using the sheep flock heredity algorithm. They considered scheduling of machines and Automated Guide Vehicles in an FMS environment [247]. Ashwani Dhingra and Pankaj Chandna aimed to deal with multi-objective flow shop scheduling problems, including sequence-dependent setup time (SDST). Their study's main objective is to minimize the weighted sum of total weighted tardiness, total weighted earliness, and makespan simultaneously. [80]. Anna Ławrynowicz improved the efficiency of the traditional scheduling methods and explored a more effective approach for solving the scheduling problem in supply networks with genetic algorithms (GAs). He developed two methods with GAs for detailed production scheduling in supply networks. The first method adopted a genetic algorithm to job shop scheduling in any node of the supply network. The second method was developed for collective scheduling using a modified genetic algorithm in an industrial cluster. The objective was to minimize the total makespan. These proposed methods were verified by using some experiments [165].

The application of the genetic algorithm to the multi-objective scheduling problem has given optimum solutions for the allocation of jobs to the machines to achieve nearly equal utilization of machine resources. Further, the makespan, as well as total machining time, is also minimized [7]. There is another type of scheduling problem is the economic lot scheduling problem which is an important scheduling problem that has been studied since the 1950s. Feasible analytical closed-form solutions were difficult to achieve. But with the help of heuristic algorithms, we can obtain good and acceptable solutions [48].

Fuzzy job-shop scheduling problems (Fuzzy JSSPs) are a class of combinational optimization problems are known as non-deterministic polynomial-hard problems. Salwani Abdullah et al. reviews the classification of Fuzzy JSSPs, constraints and objectives investigated in Fuzzy JSSPs, and the methodologies applied in solving Fuzzy JSSPs [4]. Kuroda and Wang classified fuzzy JSSPs into three main classes, namely, fuzzy JSSPs with the fuzzy due date, fuzzy JSSPs with fuzzy processing time, and fuzzy JSSPs with both fuzzy processing time and fuzzy due date [162].

Fuzzy flexible job-shop scheduling problems assign each operation to an appropriate machine and sequence the operations on the machines to minimize fuzzy makespan as its objective function [95]. Jing Huang et al. proposed a dispatching rule-based genetic algorithm with fuzzy satisfaction levels to solve the multi-objective manufacturing scheduling problem. The objective was to develop a decision-making platform that appropriately handles conflicts among different performance measures in a manufacturing system. The proposed method focused on a job shop scheduling problem to minimize the makespan, average flow time, maximal tardiness, and total tardiness [125].

Many real-world manufacturing systems are characterized by limited production capacity and tight delivery requirements [215, 289] Consequently, the manufacturer usually has to reject a certain number of jobs that require long processing time but contribute little to firm revenue [43]. This is particularly true for make-to-order manufacturers. Such scheduling problems are known as machine scheduling with job rejection [236].

Junkai Wang et al. proposed a novel multiple-objective model for batch scheduling of an energy-intensive manufacturing process, e.g., heat treatment. The model minimizes energy consumption and total weighted tardiness while considering the arrival times of each workpiece and the inherent uncertainties in gas heating values, processing times, and due dates [268].

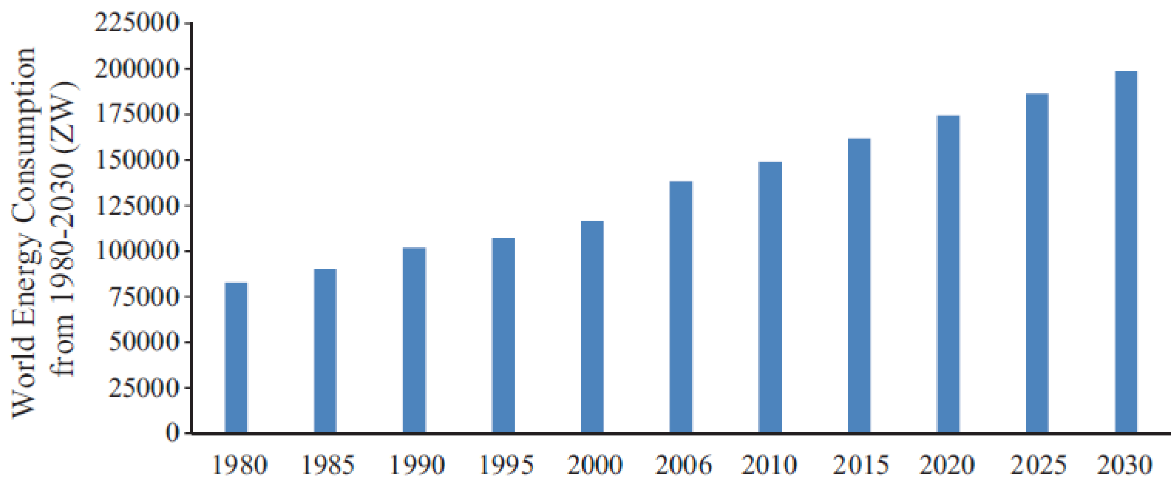


Fig. 2.3 World marketed energy consumption from 1980 to 2030 (ZW) [3]

Castro P.M. et al. address the scheduling of continuous single-stage multiproduct plants with parallel units and shared storage tanks [42]. Dai M. et al. proposes an energy-efficient model for flexible flow-shop scheduling (FFS) [251]. Sun Hoon Kim & Young Hoon Lee suggested an iterative algorithm using an optimization and simulation model for the integration of production planning and scheduling for semiconductor fabrication. The proposed model can consider a flexible manufacturing system with non-identical resource and stochastic parameters [155]. Ali Bozorgi et al. proposed a fuzzy-game theoretic model for the unit maintenance scheduling problem and pointed out the peak load and cost coefficients, which are assumed to be known in previous models, which is not realistic.

They applied fuzzy values for peak load and cost coefficients, to model the problem in a more realistic manner [35].

Haijun Wen et al. developed a hybrid intelligent algorithm including random simulation technique, neural network, and genetic algorithms to optimize an integrated remanufacturing production planning and scheduling system. They also generated a random variable samples matrix through a random simulation technique and a trained neural network. The welding scheduling problem is important in welding production. To satisfy the needs of dynamic production, three types of dynamic events, namely, machine breakdown, a job with poor quality, and job release delay, are considered. Furthermore, controllable processing times, sequence-dependent setup times, and job-dependent transportation times are also considered [279]. A model for the multi-objective dynamic welding scheduling problem (MODWSP) is formulated by Chao Lu et al. The objectives are to minimize the makespan, machine load, and instability simultaneously. Secondly, they develop a hybrid multi-objective grey wolf optimizer (HMOGWO) to solve this MODWSP [185].

Today's sustainable scheduling is the need of many manufacturing companies and energy is the main concern regarding sustainability, Christian Gahm et al. developed a research framework for energy-efficient scheduling [106]. A framework to analyze energy consumption characteristics in machining manufacturing systems from a holistic point of view is proposed by Li, Y., He, Y., Wang, Y., Yan, P., & Liu, X. [171].

Hao Luo et al. discussed the implementation of RFID technologies, which enable the shop floor visibility and reduce uncertainties in the real-time scheduling for hybrid flow-shop (HFS) production. Standard HFS approaches are difficult to be applied in real-life mold and die manufacturing schedules since most of them are offline scheduling. The off-line scheduling assumes that all jobs are available before the starting time. The information about all stages and machines is completely known in advance. Once a schedule is generated, all jobs can be continuously processed without any interruptions. The real-time visibility and interoperability, which are core characteristics of ubiquitous manufacturing, created an opportunity to minimize the uncertainty and disturbance during the production process and close the loop of production planning scheduling and execution [187].

Duflou, J.R et al. deal with energy and resource efficiency increasing methods and techniques in discrete part manufacturing [84]. Ripon K. Chakrabortty considered resource-constrained project scheduling problems with known deterministic renewable resource requirements but uncertain activity durations. [44].

According to the 5th global productivity study of the proudfoot consulting, 37% of working time is wasted, which is mainly due to a lack of planning and control [78]. Xu Gong et al. formulates a mixed-integer linear programming model for energy and labor aware production scheduling at the unit process level, considering all the conventional production constraints besides the due date [113]. Priyantha Devapriya et al. address an integrated production and distribution scheduling problem with a perishable product in which the product has a limited lifetime. A mathematical programming model based on mixed-integer linear programming was developed and then resolved [79].

Today's Research is based on reducing the energy consumption of manufacturing processes on the machine level and the product level by using optimum schedule [118, 145, 201]. Also, the higher energy cost and the growing concern over global warming have produced greater concern toward reduction for the energy consumption. Most existing research on reducing manufacturing energy consumption has focused on developing more energy-efficient machines or machining processes at the machine and the factory level [34, 120].

E.A. Abdelaziz et al. presented a comprehensive literature review about industrial energy saving by management, technologies, and policies [3]. Artigues, C. et al. deals with production scheduling involving energy constraints. They proposed a two-step integer/constraint programming method by using an industrial case study [18]. G. May et al. proposed a multi-objective scheduling model based on a green genetic algorithm that is related to energy consumption and makespan in a job-shop system and also obtained a series of different Pareto front solutions for it [191].

Dunbing Tang et al. proposed a novel algorithm based on an improved particle swarm optimization approach to address the dynamic scheduling problem reducing energy consumption and makespan for a flexible flow shop scheduling [251]. These scheduling problems are more complex than static scheduling problems and they are strongly NP-hard [94, 288]. J. Escamilla et al. built a model based on a genetic algorithm involving energy consumption and makespan in an extended version of the job-shop scheduling problem where each machine can work at different rates [89]. Z. Jiang et al. developed a multi-objective genetic algorithm based optimization model that minimizes makespan, processing cost, energy consumption and enhancing processing quality for a flexible job-shop scheduling problem [140]. Y. Liu et al. proposed a genetic algorithm-based scheduling model that minimized the total non-processing electricity consumption and total weighted tardiness for the job shop problem [179].

G. Mouzon et al. developed dispatching rules & multi-objective mathematical programming model for the minimization of the energy consumption of manufacturing equipment & total completion time. There can be a significant amount of energy savings when non-bottleneck (i.e. underutilized) machines/equipment is turned off when they will be idle for a certain amount of time [203]. Some researches focus on the energy consumption for machining manufacturing considering alternative routes with different energy characteristics for the same job [68, 119]. Other researches focus on the scheduling problem with alternative process plans in a dynamic flexible job shop [226].

To promote sustainability in unit manufacturing processes, S. Kara et al. proposed a mix-integer linear programming model to perform energy-cost-aware production scheduling for a single machine. Coupled with a genetic algorithm, the scheduling model was further applied to allocating jobs to a surface grinding process [112]. Niki Kousi et al. discussed the implementation of a service-oriented architecture that would enable the dynamic scheduling of material supply operations in an assembly system, using Mobile Assistant Units [159]. Samuel Rosat et al. showed the strong potential of primal algorithms for the crew scheduling problem, which is a key challenge for large airlines [234].

Some researchers take the job processing time as a variable for the research on rescheduling in a production environment, these researchers are [178, 271, 301]. Yong-Chan Choi (2016) focuses on a single machine scheduling problem with the sequence-dependent setup times and energy requirements to minimize average energy consumption (with machining and non-machining) as well as mean tardiness for the jobs of multiple types with dynamic arrival over time [67]. Said Mahnut Cinar developed hierarchical fuzzy logic controllers to improve the energy efficiency and cutting rate stabilization of natural stone block-cutting machines [72]. Quan Zhou et al. introduced design scheduling algorithms for use in the data broadcast environment [303]. Sojung Kim et al. proposed a simulation-based machine shop operations scheduling system for minimizing the energy cost without sacrificing productivity [154]. Reducing energy consumption is becoming a more and more essential consideration for sustainable manufacturing. Lei Li et al. proposed an operation scheduling approach for a multi-hydraulic press system to explore the potential of energy saving at the system level [170].

Chao Lu et al. investigated energy-efficient permutation flow shop scheduling problems with sequence-dependent setup and controllable transportation time from a real-world manufacturing enterprise and multi-objective mathematical model considering both makespan and energy consumption is formulated based on a comprehensive investigation

[184]. Xiuli Wu and Yangjun Sun formulated an energy consumption model for the flexible job-shop scheduling problem when the two energy-saving measures are under consideration and a genetic algorithm based on a green scheduling heuristic is developed for optimizing the makespan, the energy consumption, and the numbers of turning-on/off machines simultaneously [285].

Guiliang Gong et al. proposed a multi-objective optimization mathematical model for an original double flexible job-shop scheduling problem, in which both workers and machines are flexible. This problem considers processing time indicators, green production indicators, and human factor indicators [110]. Xuxia Zou et al. determined production scheduling and vehicle routing, which are two interacted decisions, to minimize the maximum order delivery time, and the proposed genetic algorithm is capable of providing high-quality solutions by determining the two decisions simultaneously [304]. The increase in energy costs especially in the manufacturing system encourages researchers to pay more attention to energy management in different ways. Mohammad Mohsen et al. investigate a non-preemptive single-machine manufacturing environment to reduce total energy costs of a production system [5].

Luca Zeppetella et al. proposes two mixed-integer linear programming models (for both the lost sale case and the backorder case) for optimizing the production schedule by jointly considering capacity and production constraints, and costs on one hand, and demand substitution issues on the other hand [296]. Liang-Liang Fu et al. proposed mathematical models for decentralized scheduling problems, where a production schedule and a distribution plan are built consecutively. They also developed a two-phase iterative heuristic to solve the integrated scheduling problem [104]. Alessandro Agnetis et al. described a problem that finds a production schedule of the jobs, a partition of jobs into delivery batches, and an assignment of delivery batches to vehicles so that jobs are delivered within their deadlines and total costs are minimized [6].

While finding optimal solutions for complex scheduling problems, meta-heuristics give good performance with affordable computational effort. This gives an edge to researchers when researching industrial cases such as energy-efficient production planning [107]. Paz Perez-Gonzalez & Jose M. Framinan focuses on two situations of scheduling arising in most real-life manufacturing environments. In the first case, once a set of jobs has been scheduled; their schedule cannot be modified (‘frozen’ schedule). This implies that, when the next set of jobs is to be scheduled, the resources may not be fully available.

Another option, the schedule of the previously scheduled jobs can be modified as long as it does not violate their due date [220].

Recently many manufacturing organizations are using an automated scheduling system. But the design of a fast and computerized scheduling system that gives high-quality results and requires minimal resources is a difficult task [102]. The economic lot scheduling problem (ELSP) is a problem that occurs in many production situations such as bottling, plastic production, textile production, paper production, among other operations. Nodari Vakhania et al. consider the problem of scheduling a set of jobs having only two possible processing times on a set of unrelated parallel machines and it is a generalization of the much more common problem of scheduling equal-length jobs on identical machines which may occur in the production of two different types of products [264].

J. Wang et al. presented a dynamic approach to reduce tardy jobs through the integration of process planning and scheduling in a batch-manufacturing environment and also aims at developed a schedule with fewer tardy jobs with process plan solution space of the tardy jobs [269]. T'kindt Vincent focused on just-in-time principles and detailing how they can be applied to the scheduling stage of a manufacturing process using multi- criteria models [265]. Shlomo Karhi & Dvir Shabtay solved a single-machine flexible scheduling problem, to minimize resource consumption cost with a bound on scheduling plus due date assignment penalties where both job processing times and due dates are decision variables to be determined by the scheduler [147].

Rachid Benmansour et al. studies the single machine scheduling problem for minimizing the expected total weighted deviations of completion times from random common due dates [30]. Yan Zuo, Hanyu Gu & Yugeng Xi focuses on a job-shop scheduling problem with multiple constraint machines [305]. Mehmet Oguz Atan & M. Selim Akturk solves the single CNC machine scheduling problem with controllable processing times and maximizing the total profit that is composed of the revenue generated by the set of scheduled jobs minus the sum of total weighted earliness and weighted tardiness, tooling, and machining costs [21]. Xiao Wu et al. minimized the weighted sum of tardiness cost and extra energy consumption cost using a mixed integer linear programming model [284].

**2.2 Literature Review based on Fuzzy logic**

Wen et al. developed a dynamic routing method using fuzzy logic based on the part-family formation approach. It was combined with a certainty factor procedure and help in finding the favorable route in multicellular FMS. They developed a simulation model for comparing the performance of the proposed dynamic routing approach with the fixed routing approach and used only one dispatching rule i.e. FCFS in the model [280]. Yu et al. presented a fuzzy inference rule-based scheduling approach with multiple objectives for FMS. It consists of dynamic and different preference levels. Dynamic preference levels mean priority given to different objectives can change depending on the production environment conditions like many customer orders. They have considered two objectives absolute slack and mean flow time. It was proposed that the inference fuzzy rule had a robust performance working under a heavy workload [291].

Kostas Metaxiotis et al. discussed the key role of fuzzy logic in DSSs and presented a new application of FL into DSSs in various sectors and identify new challenges for further research [193]. A.W. Labib and M.N. Yuniarto solved the problem of real-time control and monitoring of a failure-prone manufacturing system in an optimum and intelligent way. Their study also aimed to fill the gap between production systems and maintenance systems. SCADA system with fuzzy logic control is used for monitoring failure-prone manufacturing systems [163].

Pratesh Jayaswal et al. provided a brief review of recent developments in applications of ANN, Fuzzy logic, and wavelet transform in fault diagnosis. The purpose of their work was to provide an approach for maintenance engineers for online fault diagnosis through the development of a machine condition-monitoring system [138]. Rostamzadeh and Sofian present a fuzzy decision-making approach for prioritizing effective 7Ms (Management, Manpower, Marketing, Method, Machine, Material, and Money) to improve production systems performance [235]. Ming-shell et al. proposed a dynamic dispatching strategy for multiple performance measures based on fuzzy inference. [186].

Imtiaz Ahmed and Ineen Sultana developed a performance evaluation model using the fuzzy approach for all types of an organization where performance evaluation is significantly important for staff motivation, behavior development, attitude, communicating, aligning individual and organizational aims, and developing positive relationships between staff and management [9]. A new fuzzy formulation of EV charge optimization for a parking lot considering the market and EVs mobility uncertainties was proposed. The uncertainties of the market and EVs mobility were modelled using fuzzy sets [90].

Many membership shapes have been proposed by the researchers [168, 169, 207]. Klir et al. introduced the mathematical representations for several membership functions such as triangular, trapezoidal, Gaussian, bell-shaped membership function, etc [156]. Among the commonly used MFs, the triangular membership function is the popular one due to the design simplicity as this is formed using straight lines. The motivation and rationale to use the triangular membership functions were first reported by Pedrycz [217]. Triangular membership functions are the specialized form of the trapezoidal membership functions, which have been extensively used in the literature for various applications [115, 141, 174, 199, 205, 283].

Tai-Sheng Su developed a fuzzy multi-objective linear programming model that simultaneously minimizes total costs, lead time, and $CO_2$ emissions concerning multiple products and joint components. The proposed model evaluates cost-effectiveness, lead time, and $CO_2$ emissions while integrating multi-products, multi-suppliers, multi-components, joint components, and multi-machines into one remanufacturing production system [246].

Satish Tyagi et al. (2017) proposed an extended fuzzy analytic hierarchy process approach to determine the ranking in which any product development phase is influenced by socialization-externalization-combination-internalization modes [262].

The advantage of fuzzy set theory is in dealing with the ambiguity intrinsic to the decision-making problems and the ability to define vague data using classes and grouping with boundaries [209].

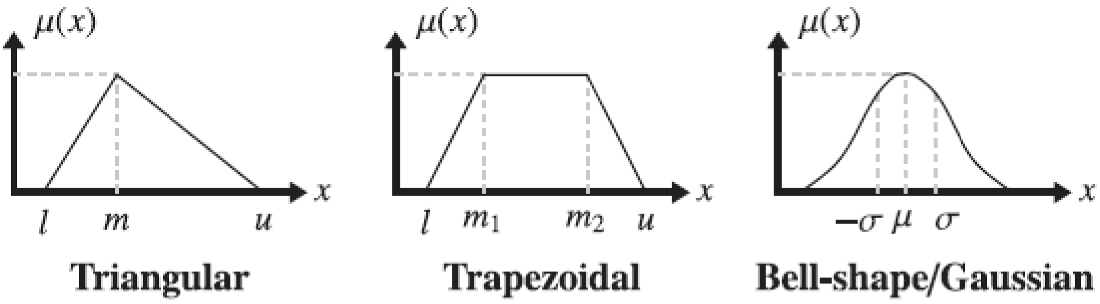


Fig. 2.4 Traditional membership functions [209]

### 2.3 Literature Review based on Scheduling using Fuzzy logic approach

C. Lowe and J. D. Tedford proposed a scheduling system using fuzzy logic to solve the multi-criteria problem. Also, the system was designed to be implemented using readily available software tools and through the use of fuzzy systems [183].

J. D. Tedford and C. Lowe developed the system, using the combined methodology of fuzzy logic and genetic algorithm which was tested on a discrete event simulation model. This system showed measurable benefits against commonly implemented dispatching heuristics in schedule performance [254].

Whenever we use some set of resources like material, labour, and equipment for making a different variety of products in a given interval of time then a problem arises called scheduling [242].

S.A. Oke and O.E. Charles-Owaba addressed the simultaneous scheduling of resource-constrained maintenance and operations and capture the uncertainty in the development of a model that schedules both preventive maintenance and operational activities. Fuzzy logic is employed to transform the human expertise into IF-THEN rules [213].

Restrepo I.M, Balakrishnan S. proposed a fuzzy logic-based methodology for generating the sequence of part movements in a multi-product batch processing through a computerized machine cell. [230].

Hao-Cheng Liu and Yuehwern Yih focused on the liquid crystal injection scheduling problem, which is divided into two sub-problems: automated guided vehicle dispatching and Liquid crystal Injection machine scheduling. First, the sub-problem is solved using a fuzzy-based method called the self-adjusted fuzzy method and the second sub-problem is solved using a modified least slack time method [177].

Jamal Hosseini Ezzabadi et al. presenting a new integrated approach based on a model using fuzzy logic, AHP technique, and operations research model to improve the organization's excellence level by increasing the quality of business performance evaluation and determining improvement projects with high priority [123].

Fang, K.-T., & Lin, B.M.T. addresses a scheduling problem in a multiple-machine system to minimize tardiness penalty and power cost [93]. Susmit Bagchi et al. (2016) proposed a novel estimation model based on probability and fuzzy logic to estimate the resource affinity pattern of a process [26]. The fuzzy set approach has been successfully applied to flow-shop and job-shop scheduling problems [83, 130, 131]. Also, a fuzzy approach to scheduling problems for software development was introduced by Wang X. and Huang W [275].

The fuzzy number approach requires the empirical acquisition of membership functions related to the degree that activity duration belongs to a fuzzy set duration. Besides experienced project team managers are usually able to specify the most and least possible/designated values for ready-time and deadline that can be also flexible [121].

Heinrich Rommelfanger suggested a common representation of fuzzy numbers using a 6-point piecewise linear membership function to ease and facilitate the acquisition of expert information, where a project manager has to provide 3 α-cuts and their corresponding activity duration intervals [233].

Kuo and Yang introduced the time-dependent learning effect in their work and they proved that the SPT dispatching rule assures an optimum schedule while minimizing total completion time on a single machine [161].

Moghaddam et al. proposed a single machine problem that has two objectives: minimizing the total weighted tardiness and minimizing the makespan. They constructed a fuzzy multi-objective linear programming model to solve the problem [252].

In real-world scheduling, the processing time of a job cannot be known precisely, and hence the completion time can only be obtained ambiguously. The fuzzy job-shop scheduling problem considers the processing times or the due dates to be fuzzy variables [198].

Scheduling involving setup times/costs plays an important role in today's modern manufacturing and service environments for the delivery of reliable products on time. The setup process is not a value-added factor, and hence, setup times/costs need to be explicitly considered while scheduling decisions are made to increase productivity, eliminate waste, improve resource utilization, and meet deadlines [13].

Wang and Liu considered the group scheduling on a single machine with deteriorating setup and processing times where both setup and processing times are increasing function of their starting times. Their primary objective is to minimize the total weighted completion time while the secondary objective is to minimize maximum cost. They presented a polynomial-time algorithm [270]. Merkert et al. discussed the main problems and potential benefits related to energy-efficient scheduling in industrial sectors [192].

A novel dynamic optimization framework is presented for integration of design, control, and scheduling for multi-product processes in the presence of disturbances and parameter uncertainty. This framework proposes an iterative algorithm that decomposes the overall problem into flexibility and feasibility analyses [158].

Yiyong Xiao & Abdullah Konak study the time-dependent vehicle routing & scheduling problem with CO2 emissions optimization and develop an exact dynamic programming algorithm to determine the optimal vehicle schedules for given vehicle routes. A hybrid solution approach that combines a genetic algorithm with the exact dynamic programming procedure is proposed as an efficient solution approach for this [286].

Guo-Sheng Liu et al. address a fuzzy flow shop scheduling problem in a production system that deals with dispatching jobs to the machines and determining the job sequence and state transition of each machine to minimize energy consumption and tardiness [175].

Juan José Palacios et al. tackled a variant of the job shop scheduling problem with uncertain task durations modelled as fuzzy numbers and minimize the schedule's fuzzy makespan and maximize its robustness [143]. Fuzzy sets help the researchers in diminishing the interlude between the classical techniques and real-world user needs [82, 281].

### 2.4 Literature review based on material selection

The material selection problem is considered as an MCDM problem and it is solved by considering all multiple conflicting criteria [176]. A. S. Milani et al. applied the MCDM approach for material selection of plastic gear with the life cycle assessment [195]. Navneet Gupta also used the MADM approach for the material selection problem of thin-film solar cells [116]. C. Bhowmik et al. adopted the TOPSIS technique for energy-efficient material selection and used sensitivity analysis for validating the results [32]. S. Jajimoggala et al. utilized an MCDM approach for the material selection of impeller using the TOPSIS technique[136]. I. P. Okokpujie et al. utilized the AHP and TOPSIS technique for wind turbine blade material selection [214]. Mohammed F. Aly et al. proposed an integrated Fuzzy geometric mean method -TOPSIS model for material selection and design concept [14]. A. Kelemenis et al. adopted the TOPSIS technique for the personnel selection and enhanced the organization performance[148]. A. Tiwary et al. utilized the fuzzy TOPSIS for the parameter selection of the micro-EDM process [257].

Emma Mulliner et al. considered the comparative analysis of various MCDM approaches such as AHP, TOPSIS, COPRAS, the weighted sum model, and the weighted product model for sustainable housing affordability[206]. S. H. Mousavi-Nasab et al. adopted MCDM approaches such as DEA, TOPSIS, and COPRAS for material selection problems [202]. Stelios H. Zanakis analyzed the performance using a simulation comparison of ELECTRE, TOPSIS multiplicative exponential weighting, simple additive weighting, and AHP [294]. Metin Dagdeviren selects the best equipment among many alternatives using the AHP and PROMETHEE and this proper selection increases the productivity, flexibility, precision, and product quality [75].

L. Anojkumar et al. adopted the comparative MCDM analysis approach for material selection of pipes in the sugar industry [17]. A. Shanian et al. applied the TOPSIS technique for the material selection of metallic bipolar plates [237]. Mehtap Dursun et al. employed a fuzzy COPRAS method for material selection for the detergent manufacturers [85]. M.F. Ashby et al. described that there is a material selection option is between 40,000 to 80,000 and almost 1000 ways to process them which shows that the material selection problems are complex and challenging. They also show the selection strategies for materials and processes [19]. P. Chatterjee et al. used the COPRAS and ARAS techniques for gear material selection [51]. P. Chatterjee et al. also applied the four MCDM techniques together for gear material selection problems. These four MCDM techniques are extended PROMETHEE II, COPRAS, ORESTE and OCRA methods [52]. V. M. Athawale et al. solved the material selection problems using UTA method. This method is one type of MCDM tool used for solving the various complex material selection problems [22]. S. Chakraborty et al. applied the three MCDM approaches such as TOPSIS, VIKOR, and PROMETHEE for five material selection problems. They also showed that the choices of the final selection depend on the criteria weights [46]. S.R. Maity et al. used the fuzzy TOPSIS for material selection of grinding wheel abrasive [189]. M. Ilangkumaran et al. adopted the hybrid MCDM approach for material selection of automobile bumper. They applied the fuzzy AHP, PROMETHEE I and PROMETHEE II for ranking of the materials [128]. S. Chakraborty considered the MOORA methodology for robot selection, flexible manufacturing system selection, CNC machine selection, and manufacturing process selection in manufacturing environments [45].

Material selection can also be done by utilizing the statistical tools e.g. Taguchi method, response surface methodology, or multiple linear regression [211]. T. A. Enab et al. used the finite element method for the material selection of the tibia tray component of the cemented artificial knee [87]. K. Fayazbakhsh et al. applied the Z-transformation in statistics for materials selection in mechanical design [97]. Fehim Findik et al. adopted the weighted property index method for the material selection problem of low weight wagon design [99]. Ali Jahan et al. used the linear assignment method with the MCDM approach for the material selection of an engineering component [135]. R. Sarfaraz Khabbaz et al. adopted the Fuzzy logic approach for materials selection in mechanical engineering design [151].

The past studies show that most of the researchers have successfully applied the MCDM approach for solving the material selection problem. After reviewing the existing literature, it is found a material selection of crankcase cover in the automobile industry is an untouched area of research. The above studies also show that TOPSIS and MOORA methodologies are effective in the identification and selection of the best material for a particular product. Therefore, the present study initially aims to identify the material available for the crankcase cover using experts from the automobile industry. Later, TOPSIS methodology is applied for material selection of crankcase cover and its results are validated using the MOORA and PROMETHEE methodology.

**2.5 Literature review based on the various dispatching rules**

Production managers face difficulties in optimizing resource utilization as well as on-time delivery of products [7]. With these SPT, EDD, CR techniques, and other techniques, we can optimize resource utilization and on-time delivery together. Dispatching rules can be effectively used in job sequencing problems in single machine scheduling and can also include parameters like setup time and energy consumption [67]. Selected criteria of a performance play a significant role in the results obtained through these dispatching rules. Effective results can also be obtained through the set of manufacturing orders scheduled [114]. Dispatching rule-based research by various authors is shown in Table 2.2.

Table 2.2 Dispatching rule-based research by various authors

| Authors | Problem Type | Factors/ Parameters | Dispatching Rule Used | Approach used |
|---|---|---|---|---|
| Grabot B. et al. [114] | Job-shop scheduling | Lateness, Tardiness, Flow time, Average lateness | SPT or the slack time rule | Fuzzy simulator |
| Jeong K.C. et al. [139] | Real-time scheduling | Mean flow time, Mean tardiness, | FCFS, SPT, SRW, EDD, MDD, MOD, COVERT, ATC | Real-time scheduling mechanism |
| Huang J. et al. [125] | Job shop scheduling | Makespan, Average flow time, Maximal tardiness, Total tardiness | SPT, EDD, LRP, LRP/OP, LPT, MOR, MRP, MRP/OP, and HOLD | Genetic Algorithm, Fuzzy logic |
| Lu M. S. et al. [186] | Dynamic dispatching | Due date, Total Processing time, mean flow time, mean tardiness, Mean earliness | SPT, EDD, SPT×TOT, LUS, NINQ | Fuzzy logic |
| Choi Y.C. et al. [67] | Dynamic Scheduling | Sequence-dependent setup times and energy requirements | ATC with Setups and Machining Energy consumption | Dispatching rule-based scheduling algorithms |

Lu et al. studied the dynamic dispatching problem using a fuzzy approach under several performances affecting variables. First, the fuzzy inference rule base is developed using performance variables. Then, using this rule base best dispatching rule is selected [186]. Choi et al. considered single machine scheduling problems under energy and set up time constraints with the objective of minimization of mean tardiness and energy consumption [67]. Pfund et al. considered unrelated parallel machine scheduling under stochastic uncertainty with the objective of minimization of makespan, machine utilization, finishing time, and over time [221]. Zuo et al. solved the job shop scheduling problem using scheduling methods based on several machine constraints. They first identify the constraint and non-constraint machines. Then, used a developed method to get a balanced solution of solution quality and time [305].

Restrepo et al. considered flexible manufacturing cell scheduling using a comparative approach between the fuzzy set approach and dispatching rules like SPT and WEED with the fuzzy strategy of the fuzzy machine and fuzzy job [230]. Mouzon et al. minimized energy consumption by proposing dispatching rules and utilizing a mathematical programming model [203]. Abd et al. utilized dispatching rules, sequencing rules, due date tightness, and cell utilization for the dynamic scheduling problem. These dispatching rules are SNQ (smallest number in queue), SIO (shortest imminent operation time), and WINQ (least work in queue). Cell utilization and due date are identified as the most significant factor for scheduling problems [2]. Atan et al. solved the single CNC machine scheduling problem to maximize the overall profit using the heuristic algorithm [21]. Wang Y et al. analyzed the performance of priority rules considering stochastic variables using a full factorial experiment [276]. Chiang TC et al. solved the due date-based job shop-scheduling problem using eighteen dispatching rules [64].

Dispatching rules have an advantage than other method and rules because it requires minimum information and computational effort [108, 153]. Kianfar et al. formulated a mixed-integer programming model for minimizing rejection and tardiness cost of jobs in the dynamic flow shop scheduling system by comparing four dispatching rules from literature to the new proposed four dispatching rules [152]. If a part or job is manufactured before the due date, then it incurs earliness cost and if it manufactures after the due date, it incurs a penalty. So most of the researchers follow the objective to manufacture part or job as close as the due date [255]. From the above-reviewed literature, we found out that the common objectives in scheduling problems are to minimize the makespan, energy consumption, machine utilization, finishing time, overtime, setup time, rejection cost, and tardiness cost [67, 152, 221].

### 2.6 Literature review based on the energy consumption scenario

Today's energy-efficient scheduling is the indispensable need of many manufacturing companies. Gahm, Denz, Dirr, & Tuma [106] developed a research framework for energy-efficient scheduling. A framework to analyze energy consumption characteristics in machining manufacturing systems is given by Y. Li, He, Wang, Yan, & Liu [171].

Energy saving in the industry can be done in the following ways:[3]

1. Energy-saving by management
2. Energy-saving by technology
3. Energy-saving by policies and regulations

Energy-saving by management and technology is shown in Fig. 2.5 and Fig. 2.6.

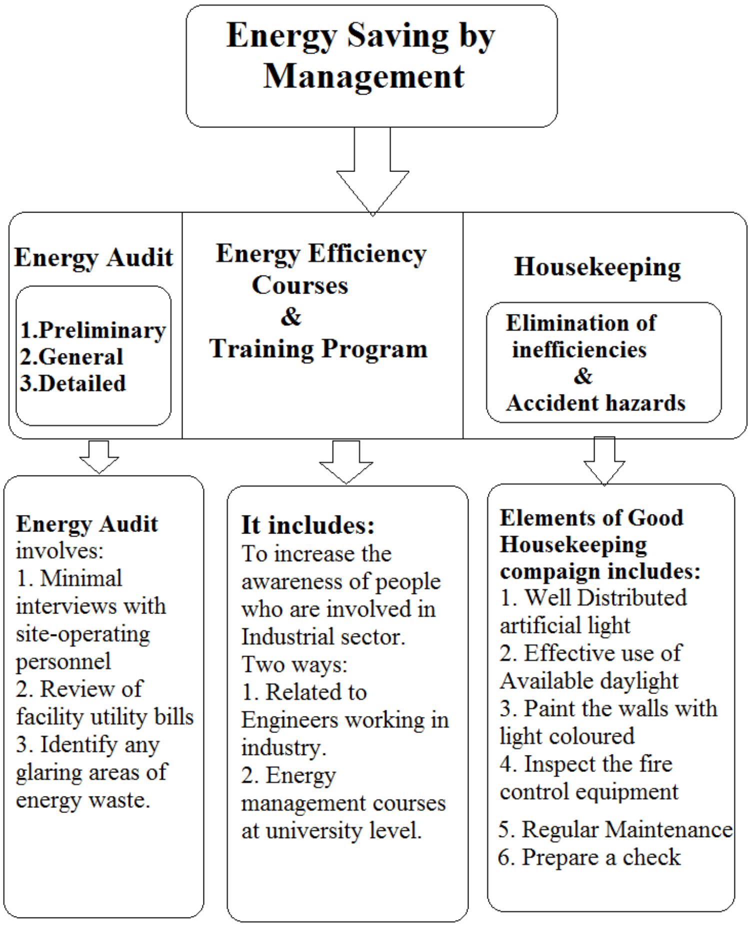


Fig. 2.5 Energy-saving by management [3]

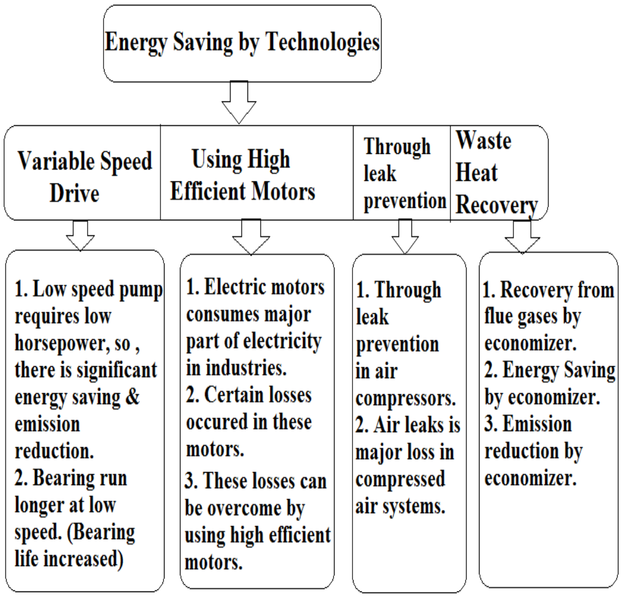


Fig. 2.6 Energy-saving by technologies [3]

Energy-efficient scheduling problems (EESP) deals with the reduction of energy consumption parameters and all these studies are deterministic [98, 268, 278, 298]. Makespan and energy consumption are the main parameters in these studies which must be balanced to achieve an energy-efficient environment [190].

Table 2.3 Summary of conducted research on EESP

| Author name | Approaches | Techniques | Scheduling Type | Parameter optimized |
|---|---|---|---|---|
| J. Wang et al. [268] | Metaheuristic Approach | Fuzzy Logic | Batch scheduling | Energy consumption, tardiness |
| Aghelinejad et al. [5] | Metaheuristic Approach | Genetic Algorithm | Production scheduling | Energy cost |
| Yan et al. [287] | Metaheuristic Approach | Genetic Algorithm | Flexible flow shop scheduling | Energy consumption, Makespan, cutting energy, Cutting times |
| May et al. [191] | Metaheuristic Approach | Genetic Algorithm | Job shop scheduling | Energy consumption, Makespan |
| Tang et al. [251] | Metaheuristic Approach | Particle Swarm Optimization | Flexible flow shop Scheduling | Energy consumption, Makespan |
| Fang & Lin [93] | Metaheuristic Approach | Particle Swarm Optimization | Parallel-machine scheduling | Tardiness penalty and power cost |
| Garcia-Santiago et al. [107] | Metaheuristic Approach | Harmony Search | Production scheduling | Energy consumption |
| Dorry [81] | Hybrid/Cluster Approach | Hybrid Fuzzy PSO Approach | Steelmaking-Continuous Casting Scheduling | Waiting time of charges |
| Lu, Gao, Li, Pan, & | Hybrid/Cluster | Hybrid | Flowshop | Energy consumption, |

| | | | | |
|---|---|---|---|---|
| Wang [184] | Approach | backtracking search algo. | scheduling | Makespan |
| Liu, Lohse, Petrovic, & Gindy [181] | Hybrid/Cluster Approach | Non dominant Sorting Genetic algo. | Job shop Scheduling | Total energy consumption and total weighted tardiness |
| Mokhtari & Hasani [200] | Hybrid/Cluster Approach | Evolutionary Algorithm | Job-Shop Scheduling | Total energy cost, Total completion time, Total availability |
| Jiang, Zuo, & Mingcheng [140] | Hybrid/Cluster Approach | Non dominant Sorting Genetic algo. | Job-shop Scheduling | Energy consumption, Makespan, Processing cost |
| Wu & Sun [285] | Hybrid/Cluster Approach | Green Scheduling Algorithm | Job Shop | Energy Consumption, Makespan, No. of turning on-off machines |
| Gong, De Pessemier, Joseph, & Martens [112] | Operation Research | Mix-integer programming | Production Scheduling | Energy consumption, Demand response |
| Bruzzone, Anghinolfi, Paolucci, & Tonelli [40] | Operation Research | Operation Scheduling approach | Flexible flow shops | Total tardiness, Makespan |
| L. Li, Huang, Zhao, & Liu [170] | Operation Research | Operation Scheduling approach | Operation scheduling | Energy consumption, Makespan |
| Chen, Zhang, Arinez, & Biller [58] | Statistical Approach | Markovian analysis | Operation scheduling | Energy consumption, Productivity |
| Choi, Y.C [67] | Algorithm-Based Approach | Dispatching rule-based scheduling algorithms | Single Machine Scheduling | Average Energy consumption, Mean tardiness |
| Lee S et al. [166] | Algorithm-Based Approach | Dynamic control algorithm | Single Machine Scheduling | Energy consumption, Total penalty cost |
| Merkert et al. [192] | Literature review papers | Review Paper | Energy Aware Scheduling | Energy consumption, Energy Efficiency, Profit |
| Duflou et al. [84] | Literature review papers | Review Paper | Energy efficient Scheduling | Energy Efficiency, Resource efficiency |
| Gahm et al. [106] | Literature review papers | Review Paper | Energy efficient Scheduling | Energy demand, Energy supply, Energetic Coverage |

Most of the researchers have used different metaheuristic techniques to solve various scheduling problems. The most preferred metaheuristic techniques are fuzzy logic and genetic algorithm [5, 191, 268, 287]. Fuzzy logic best deals with data uncertainty and incomplete information [208]. Table 2.3 summarizes the various research and articles related to EESP.

Energy efficiency barriers are generally four types such as economic non-market failure, economic market failure, behavioral barrier, organizational barrier. Each barrier example is shown in Fig. 2.7 [259].

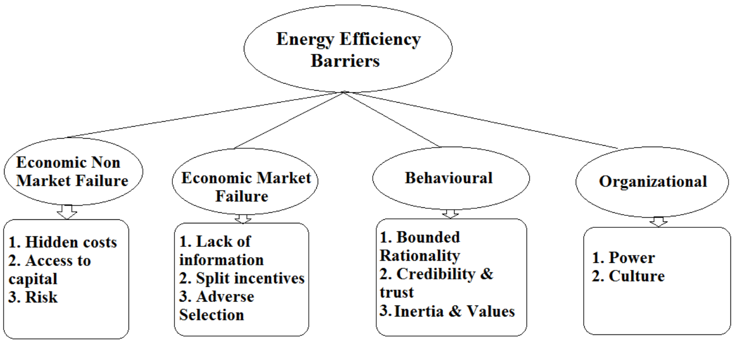


Fig. 2.7 Energy efficiency barriers [259]

Fuzzy schedule modeling has been successfully applied in manufacturing [84, 245], project scheduling [300], vehicle routing problems [274], timetabling scheduling problems [24], and several other scheduling applications e.g. casting scheduling problems of steel making [81] and nurse scheduling problems in hospitals [132]. Zhang et al. [300] analyzed the real-world project scheduling problems using the Fuzzy programming models considering the total crash cost as the objective function and parameters include are fuzzy duration, fuzzy crash time, and fuzzy completion time with possibility level $\alpha$.

The past studies show that most of the researchers have successfully applied the fuzzy approaches for solving the various scheduling problems. After reviewing the existing literature, it is found that the route selection and job prioritization of crankcase cover manufacturing in the automobile industry is an untouched area of research. The above studies also show that fuzzy-based methodologies are effective for the generation of optimum schedules in various industries. Therefore, the present study initially aims for job prioritization and route selection of the crankcase cover manufacturing using the mamdani fuzzy inference system. Later, the fuzzy set approach is applied for the validation of results.

## 2.7 Literature review based on the MCDM approaches

MCDM is a branch of operation research in dealing with complex multi-criteria or specifications. This technique helps in obtaining the best choice among the various alternatives in these fluctuating real-world problems [56]. TOPSIS technique is one of the best techniques of MCDM used by the various researchers in the past studies [56, 70, 250, 290] and this technique is combined with fuzzy logic first time by R.E Bellman et al. in dealing with uncertainty [29]. This method have been applied in reverse logistics [8], material selection [17, 189], project selection [15, 250, 253], facility location selection [88], warehouse location selection [20], plant location selection [70, 290], supplier selection [77, 142], robot selection [71, 228], maintenance management system selection [263], machine tool selection [292] and healthcare industry [41, 188].

S. Agrawal et al. utilized the fuzzy TOPSIS for prioritizing the critical factors for implementing reverse logistics [8]. R. Rostamzadeh et al. prioritized the 7Ms using this methodology for production system improvement [235]. S. Maity et al. solved the grinding material selection problem using Fuzzy TOPSIS [189]. L. Anojkumar et al. analyzed the material selection problem in the sugar industry using MCDM comparative analysis technique. They used the four MCDM techniques Fuzzy AHP, VIKOR, TOPSIS, and ELECTRE for this study [17].

Y. Tan et al. solved the project selection problem of the construction industry using fuzzy TOPSIS. They showed that the fuzzy TOPSIS is a very effective tool for all the constructors in bidding for the appropriate project [250]. M. P. Amiri analyzed the project selection problem for the development of oil fields using fuzzy TOPSIS with AHP [15]. Construction projects are dynamic in nature and consist of high risks and uncertainty. Their high risks can be effectively evaluated by fuzzy TOPSIS [253].

The warehouse location selection problem also consists of uncertainty and vagueness. M. Ashrafzadeh et al. utilized this approach for solving the warehouse location problem [20]. I. Ertugral et al. solved the facility selection location problem using Fuzzy AHP and Fuzzy TOPSIS in the textile industry [88]. MCDM approaches can also be successfully applied in solving supplier selection problem which consists of quantitative and qualitative criteria both.

DEMATEL method is another effective approach that can be applied for prioritizing the critical parameters or risk factors in the automobile spare industry [282], project management [299], waste management [53], maintenance management [266], product design [127, 173], remanufacturing [241], service quality improvement [59, 69], supplier selection [65] and production process problems [261].

Hsin-Hung Wu et al. identified the technological capability, organization, and service as the three most critical dimensions in the automobile spare industry using the DEMATEL method. They identified the five most influential criteria among thirty criteria for improvement [282]. Lin Zhang et al. identified the critical risk factors in urban projects for controlling the flooding and water shortage using the DEMATEL method. Their finding of critical factors is helpful for local government and private capitals to mitigate future risks [299].

Ankur Chauhan et al. identified and prioritized the barriers of waste recycling management using this methodology [53]. Davor Vujanovic et al. solved the vehicle fleet management problem and evaluated its indicators by ANP (Analytic Network Process) and DEMATEL method [266].

DEMATEL methodology can also be used in product design. The designing of smaller objects is a difficult task due to its limited design capacity, but DEMATEL methods can effectively use in designing a smaller object. Ahmed Ibrahim Alzahrani et al. identified the design requirements of mobile phones using DEMATEL methods [127]. Ya-Ti Lin et al. identified the seven core competencies of the semiconductor industry for IC design and find the interrelation among them using the DEMATEL method [173].

DEMATEL also helps in identifying the external barrier to remanufacturing [241]. This approach can be combined with other MCDM approaches for criteria selection for quality improvement [59]. Jianjie Chu et al. enhanced the air travel service quality by prioritizing the key service criteria using DEMATEL and gray theory [69]. Sang-Bing Tsai et al. solved production process problems using the combined model of DEMATEL with FMEA. They enhanced product quality, reliability, competitiveness, and reduced cost using this model [261].

The above studies show that scheduling parameter prioritization in the automobile industry is an untouched area of research and the fuzzy TOPSIS and DEMATEL methods are effective in the identification and prioritization of the critical parameters or risk factors of various industries problems.

## 2.8 Literature review based on the different approaches

Literature reviews based on different approaches like metaheuristic approaches and mathematical models are shown in Table 2.4 to Table 2.13.

Table 2.4 Metaheuristic approach-based scheduling classification 1

| Authors | Problem Type | Factors /Parameters | Approach | Sector | Country |
|---|---|---|---|---|---|
| C. Lowe et al. [183] | Production Scheduling | Average flow time of jobs, Total time spent in system by set of jobs, Percentage of products completed, Average lateness of jobs, | Fuzzy Logic | Manufacturing | New Zealand |
| Fortemps, P. [101] | Jobshop Scheduling | Makespan, Fuzzy duration, Centre of makespan, Spread of makespan | Fuzzy Approach | Industry | Belgium |
| Ishibuchi, H. [130] | Flowshop Scheduling | Makespan, Maximum Tardiness, No. of machine, No. of Jobs, total, Flow time | Genetic Algorithm | Manufacturing | Japan |
| Chanas, S. et al. [49] | Single Machine Scheduling | Maximum Lateness, Fuzzy Processing times, Fuzzy Due dates | Lawler's Algorithm | Industry | Poland |
| Coudert, T. [73] | Production Scheduling | Fuzzy Due date, Manufacturing time, Maintenance time, No. of activities per machine | Fuzzy logic | Manufacturing | France |
| Sudiarso, A. et al. [248] | Production Scheduling | Breakdowns Frequency, Mean number of parts, Optimal batch size, Membership Functions | Fuzzy logic | Manufacturing | Indonesia |
| Dubois, D. et al. [82] | Fuzzy scheduling | Due date, Release date, Processing time, Makespan | Fuzzy Set | Manufacturing | France |
| Metaxiotis, K.S. et al. [193] | Production Scheduling | Customer demand, High quality of products & services, Customer, Satisfaction, Reliable, delivery date, High efficiency | AI-based approach | Manufacturing | Greece |
| Oke, S.A. et al. [213] | Preventive Maintenance Scheduling | Cost of production of bolts and nuts, Cost of maintenance of Lathe machine, Cost of operation of lathe machine | Fuzzy logic | Manufacturing | Nigeria |
| C.D. Geiger et al. [108] | Single Machine Scheduling | Number of Jobs, Traffic Intensity, Due Date Tightness, Due Date Variability | Genetic Algorithm | Industry | USA |
| Srinoi, P. et al. [242] | Dynamic Scheduling | Machine Allocated processing time, Machine priority, Due date, setup time, Average machine utilisation, work in process, Mean flow times | Fuzzy logic | Manufacturing | Thailand |
| Atan, M. O. et al. [21] | Single CNC machine Scheduling | Controllable processing times, Multiple due dates, Set of scheduled jobs, Total weighted earliness, Weighted tardiness, Tooling and Machining costs | Four-stage heuristic algorithm | Manufacturing | USA |

Table 2.5 Metaheuristic approach-based scheduling classification 2

| Authors | Problem Type | Factors /Parameters | Approach | Sector | Country |
|---|---|---|---|---|---|
| Restrepo, I.M. et al. [230] | Multi-objective Scheduling | Total penalty, Part types, Total machine idle cost, Membership, function, Total processing time, Tardiness cost, Throughput time | Fuzzy logic | Manufacturing | Canada |
| Wang, J. et al. [269] | Process Planning and scheduling | Lateness, Tardiness, Operation waiting time, Batch size, Due date, Job weight | H Tardy Algorithm | Manufacturing | Singapore |
| Fattahi, P. et al. [94] | Flexible job shop | Schedule Efficiency, Schedule Stability, Processing time, Number of assigned operations to machine, Start time of operation | Genetic Algorithm | Industry | Iran |
| Ławrynowicz, A. [165] | Job shop scheduling | Most work remaining, Least work remaining, most operations remaining, Least operations remaining, Production plan, Total makespan, SPT, LPT | Genetic algorithm | Manufacturing | Poland |
| Ming-Shan Lu et al. [186] | Dynamic dispatching | Average arrival interval of jobs, Due date, Total Processing time, Mean flow time, mean tardiness | Fuzzy logic | Manufacturing | China |
| Agrawal, R. et al. [7] | Flexible Job shop Scheduling | No. of Jobs, No. of machine, Make Span time, Total machining time, Maximum Completion time | Genetic Algorithm | Manufacturing | India |
| Cesaret, B. et al. [43] | Single Machine Scheduling | Total Revenue, Sequence dependent Set up times, Release dates, Due dates, Tardiness | Tabu search | Manufacturing | Turkey |
| Chen, G. et al. [58] | Machine Startup & Shutdown Scheduling | Production rate, Work in process, Machine starvation, Machine blockage | Markovian Analysis, Greedy Algorithm | Automotive Paint Shop | USA |
| Fang, K.T. et al. [93] | Parallel Machine Scheduling | Tardiness penalty, Power cost, No. of jobs, No. of machines, Due date, Completion time, Tardiness | Particle Swarm opt. | Industry | Taiwan |
| Hao-Cheng Liu et al. [177] | Liquid Crystal Injection Scheduling | Automated guided vehicle dispatching, Tardiness of cassettes | Self-adjusted fuzzy (SAF) method | Electronics | USA |
| Santiago, C.A.G. et al. [107] | Energy efficient scheduling | Energy Consumption, Energy Efficiency | Harmony search | Industry | Spain |

Table 2.6 Metaheuristic approach-based scheduling classification 3

| Authors | Problem Type | Factors /Parameters | Approach | Sector | Country |
|---|---|---|---|---|---|
| Fadi Shrouf et al. [239] | Single Machine Scheduling | Total Energy Consumption, No. of jobs, Processing time, Idle time, Turning on & off time | Genetic Algorithm | Industry | Italy |
| Jiang, Z. et al. [140] | Job-shop Scheduling | Makespan, processing cost, energy consumption, cost-weighted processing quality, Environmental emissions | Genetic Algorithm | Industry | China |
| Liu, Y. et al. [180] | Job Shop Scheduling | Total energy consumption, Total weighted tardiness, Tardiness factor, Population size, Crossover probability, Mutation probability | Genetic Algorithm | Manufacturing | UK |
| Shen, X.N. et al. [238] | Job shop scheduling | Completion time, Due date, Operation processing time, Number of operations assigned to the machine, Job release time, Number of unprocessed and available operations left in job | Evolutionary algorithms | Manufacturing | China |
| D. Tang et al. [251] | Flexible flow shop | Energy Consumption, Makespan, No. of machine, No. of jobs, Processing time, Setup time, Spindle Speed, Unload Power | Particle Swarm opt. | Manufacturing | China |
| Knyazevaa, M. et al. [157] | Project Scheduling | Fuzzy numbers, computational time, Fuzzy plan Fuzzy resource allocation, Heuristic priority rules | Fuzzy Logic | Industry | Russia |
| May, G. et al. [191] | Job Shop Scheduling | Makespan, Energy Consumption | Genetic algorithm | Manufacturing | USA |
| Ali Bozorgi et al. [35] | Unit Maintenance Scheduling | Production cost, Peak loads, Repetitive Iterations, Peak demand | Fuzzy Framework | Electrical | Iran |
| Bagchi, S. [26] | Distributed scheduling | Overall resource utilization, Throughput, Estimation intervals, Snapshot intervals, Scheduling events | Fuzzy logic | Industry | Republic of Korea |
| Khalid Abd [2] | Dynamic Scheduling | Sequencing rule, Dispatching rule, Cell utilisation, Due date tightness | Fuzzy Logic | Manufacturing | Australia |
| Chia-Yu Hsu et al. [124] | Distributed Job Shop Scheduling | No. of Jobs, Makespan, Average flow time, Computation time, Average no. of unsatisfied Jobs | Fuzzy Constraint Directed Approach | Manufacturing | Taiwan |
| Wang, J. et al. [277] | Batch scheduling | Energy consumption, Total weighted tardiness, Processing time, Arrival time, Due dates | Fuzzy logic | Industry | China |

Table 2.7 Metaheuristic approach-based scheduling classification 4

| Authors | Problem Type | Factors /Parameters | Approach | Sector | Country |
|---|---|---|---|---|---|
| Yan, J. et al. [287] | Flexible flowshop Scheduling | Cutting energy, Cutting time, Makespan, Total Energy Consumption | Genetic Algorithm | Manufacturing | China |
| Aghelinejad, M. M. et al. [5] | Production scheduling | Time dependent energy costs, Computational time, Total number of periods, Number of jobs, Processing time, States of the machine | Genetic Algorithm | Manufacturing | France |
| Chao Lu et al. [185] | Dynamic scheduling | Job Release Delay, Processing times, Setup times, Transportation time, Makespan, Machine load | Grey Wolf Optimizer | Welding Industry | China |
| Wang, D. J. et al. [267] | Dynamic scheduling | Operational Cost, Cost of deviation | Directed Search Genetic Algorithm | Container Manuf. | China |
| Geyik, F. et al. [109] | Parallel Processor Scheduling | Production time, Welder Ability, Welder experience, Batch size, Learning effect rate, Makespan | Fuzzy logic | Welding Industry | Turkey |
| Amirian, H. et al. [16] | Project Selection Scheduling | Time-dependent profits, total cost, total unused resources | Particle Swarm opt. | Manufacturing | Iran |
| Escamilla, J. et al. [89] | Job shop scheduling | Processing time, Cost, Quality, Energy efficiency, Makespan | Genetic Algorithm | Tin Industry | Spain |
| Litoiu, M. et al. [174] | Real-time task Scheduling | Processing times, Deadlines, Fuzzy number, Optimal assignment of Priorities | Fuzzy Logic | Industry | Italy |
| Subbaiah, K. V. et al. [247] | FMS Scheduling | Makespan, Mean Tardiness, Population size, Iterations completed, Due Date, Lateness value | Sheep flock heredity algorithm | Industry | India |
| Toksan, M.D. et al. [258] | Single machine Scheduling | Learning effect, Fuzzy Processing time, Makespan, Total completion time, Total weighted completion time | Fuzzy logic | Manufacturing | Turkey |
| Xiao, Y. et al. [286] | Green Vehicle routing & Scheduling | Servicing customer Due-time, Customer Tardiness penalty coefficient, Vehicle maximum payload capacity, Vehicle maximum travel length | Genetic algorithm | Logistics | China |
| Xiuli Wu et al. [285] | Flexible Job shop Scheduling | Makespan, Energy consumption, Numbers of turning-on/off machines, Processing Speed, Ideal Speed | Genetic Algorithm | Manufacturing | China |
| Zou, X. et al. (2018) [304] | Production Scheduling & Vehicle routing | Capacity constraints, Vehicle routing, Order delivery time, Production Sequence | Genetic Algorithm | Manufacturing | China |

Table 2.8 Algorithm/ Mathematical model approach-based scheduling 1

| Authors | Problem Type | Factors /Parameters | Approach/Model | Sector | Country |
|---|---|---|---|---|---|
| Dubois, D. et al. [82] | Job Shop | No. of Jobs, set of operations, Release date, Due date | Mathematical Model | Manufacturing | France |
| Kuroda, M. et al. [162] | Job shop scheduling | Fuzzy Due date, Fuzzy Processing times, Processing Routes | Branch and bound Algorithm | Manufacturing | Japan |
| Yu, L. et al. [291] | FMS Scheduling | Decision Function, Mean absolute slack, percentage of JIT, Flow time, Average Arrival interval | Multi Criteria Decision Making | Manufacturing | Japan |
| Choi, S.H. et al. [66] | Job-shop scheduling | Processing time, Release time of operation, Delivery time of operation, Start time of operation, Makespan | Quick value-setting Algorithms | Manufacturing | China |
| Kuo, W.H. et al. [161] | Single machine Scheduling | Total completion time, Time-dependent learning effect job sequence | Mathematical model, SPT rule | Manufacturing | Taiwan |
| Oke, S.A. et al. [212] | Maintenance Scheduling | Total preventive maintenance scheduling cost, Production cost | Mathematical Model | Shipping Industry | Nigeria |
| Muhuri, P.K. et al. [205] | Real-time task Scheduling | Fuzzy deadlines, Fuzzy processing times, Membership functions | Simulation experiments | Industry | India |
| Zuo, Y. et al. [305] | Job-shop Scheduling | Release time, Earliest operation due date, non-constraint machine, Maximum lateness of jobs | Shifting bottleneck Methods | Manufacturing | China |
| Moghaddam, R.T. et al. [252] | Single machine Scheduling | Total weighted tardiness, Makespan, Decision maker Objective functions, Satisfaction degrees | Linear programming | Manufacturing | Iran |
| Capon-Garcia, E. et al. [161] | Batch Process Scheduling | Makespan, Environmental Impact, Economic Concern, Plant Profitability, Productivity | Mathematical Model | Industry | Spain |
| Castro, P.M. et al. [42] | Multiproduct plant Scheduling | Electricity Price, Power Availability, Due date, Production level | Mixed Integer linear prog. | Manufacturing | Portugal |
| Fang, K. et al. [91] | Flow Shop Scheduling | Peak Power load, Energy Consumption, Carbon footprint, Makespan | Mixed Integer Prog. | Manufacturing | USA |
| Rajabinasab, A. et al. [226] | Job shop scheduling | Stochastic job arrivals, Uncertain processing times, Unexpected Shop utilization level, Due date tightness, Breakdown level, mean time to repair | Agent-based approach | Manufacturing | Iran |
| Vincent, T. [265] | Just-in-time Scheduling | No. of jobs, No. of machines, No. of sublots per operation, Number of indivisible elements, Release date, Due date | MCDM | Manufacturing | France |

Table 2.9 Algorithm/ Mathematical model approach-based scheduling 2

| Authors | Problem Type | Factors /Parameters | Approach/Model | Sector | Country |
|---|---|---|---|---|---|
| Benmansour, R. et al. [30] | Single machine Scheduling | Expected total weighted deviations, Completion times, Common due date, Stochastic breakdowns, exponentially distributed uptimes and downtimes, early tardy penalty | Mathematical Model | Manufacturing | France |
| Bruzzone, A.A.G. et al. [40] | Energy Aware Scheduling | Tardiness, Makespan, Peak of Power | Mixed Integer Prog. | Manufacturing | Italy |
| Kamaruddin, S. et al. [144] | Production Scheduling | Average throughput time, Lateness, Labour productivity, Production rate machine, Process capability | ANOVA | Radio Cassette Industry | Malaysia |
| Yao, F.S. et al. [288] | Flow-shop Scheduling | Time complexity, Completion Time, Makespan | Polynomial Algorithms | Semiconductor Manufacturing | China |
| Artigues, C. et al. [18] | Energy Scheduling | Energy, Resource, Tardiness, Total time | Integer Programming | Industrial | France |
| C. Ozguven & B. Sungur [216] | Workforce Scheduling | Worker’s type, Work type, Worker Cost, No. of off days, Shift types, No. of workers | Integer Programming | Industry | Turkey |
| Deming Lei et al. [167] | Job-shop Scheduling | Interval carbon footprint, Makespan, Uncertainty, Heterogeneous resources | Lexicographical Method | Manufacturing | China |
| Fang Fu [103] | Project Scheduling | Inventory holding cost, Back-order cost | Mixed Integer Prog. | Construction | China |
| Fang, K. et al. [92] | Flow shop scheduling | Makespan, Peak Power consumption, Running time, No. of jobs | Mixed Integer Prog. | Manufacturing | USA |
| Fang, K.T. et al. [93] | Parallel Machine Scheduling | Tardiness penalty, Power cost, No. of jobs, No. of machines, Due date, Completion time, Tardiness | Integer Programming | Industry | Taiwan |
| Gonzalez, P. P. et al. [220] | Scheduling Policies | Common due dates, Scheduling policy, Total tardiness, Set of jobs, Makespan | Design of Experiments | Manufacturing | Spain |
| Luo, H. et al. [187] | Dynamic Scheduling | Processing time, Due Date, Makespan, Shop Floor Visibility | Multi period hierarchical Sched. | Manufacturing | China |
| Mishra, A. et al. [197] | Real Time Task Scheduling | Energy consumption, No. of task, No. of cores, Core speed, Iterations, Task Deadline | Monte Carlo Algorithm | Electronics | India |
| Vakhania, N. et al. [264] | Scheduling Unrelated M/c | Set of jobs, Processing times, Set of unrelated parallel machines, Makespan | Linear Programming | Manufacturing | Germany |

Table 2.10 Algorithm/ Mathematical model approach-based scheduling 3

| Authors | Problem Type | Factors /Parameters | Approach/Model | Sector | Country |
|---|---|---|---|---|---|
| Le Liu et al. [178] | Single machine Rescheduling | Linear deteriorating jobs, Position-based learning effects, Scheduling efficiency, Job actual processing time, maximum sequence disruption | Polynomial Solvability | Manufacturing | China |
| Gong, X. et al. [112] | Single Machine Scheduling | Machine state, Average power, Cycle duration, Due date, Electricity cost, Demand response, Energy Efficiency | Mixed-integer linear Programming | Manufacturing | Belgium |
| Jinwen Ou et al. [215] | Parallel Machine Scheduling | Job Completion time, Total Penalty of all rejected jobs Number of Jobs Accepted | Worst-Case Bound | Manufacturing | China |
| Yin, Y. et al. [289] | Single machine Scheduling | Total Completion Time, Total Rejection Cost, Average running time, Average number of states | Improved Shabtay Algorithm | Industry | China |
| Bennella, J.A. et al. [31] | Dynamic Scheduling | Runway throughput, Earliness, Lateness, Cost of fuel, Flight time | Dynamic Programming | Aircraft Industry | UK |
| Chakrabortty, R.K. et al. [44] | Project Scheduling | Deterministic renewable resource, Uncertain activity durations, Resource Capacity, Resource usage of activity for resource | Branch and Cut algorithm | Industry | Australia |
| Kim, S.H. et al. [155] | Production Planning and Scheduling | Manufacturing lead time, the number of setup events, Available work-in-process (WIP) level, Feasibility, Demand satisfaction | Linear Programming | Fabrication Industry | Republic of Korea |
| Alessandro et al. [6] | Integrated Production Scheduling | Fixed Departure time & Inventory holding cost, Batch Scheduling, Integrated logistics, Production Planning, Supply chain coordination | Assignment Problem (Lexmin Algorithm) | Manufacturing | Italy |
| Cheng, T.C.E. et al. [63] | Flow shop Scheduling | Makespan, Resource level, relocation problem, | Johnson’s algorithm | Manufacturing | Hong Kong |
| Devapriya, P. et al. [79] | Production Scheduling | Cost, Fleet size, Trucks’ routes, Product lifetime, Travel time, Capacity of each truck | Mixed Integer Linear Programming | Packaging Industry | USA |
| Gong, X. et al. [113] | Production scheduling | Energy consumption, Due Date, Labour Cost, Electricity Cost | Mixed-integer linear Programming | Plastic Bottle Manufacturing | Belgium |
| Kim, S. et al. [154] | Machine shop Operations Scheduling | Spindle speed, Feed rate, Depth of cut, Actual Average Power Consumption | Regression Analysis | Manufacturing | USA |

Table 2.11 Algorithm/ Mathematical model approach-based scheduling 4

| Authors | Problem Type | Factors /Parameters | Approach/Model | Sector | Country |
|---|---|---|---|---|---|
| Lei Li et al. [170] | Operation Scheduling | Energy Consumption, start time of process, Completion time of process, Processing sequence number, Duration of operation, Duration of process, Idling time, Energy efficiency, Makespan | Mathematical Model | Multi-hydraulic press Industry | China |
| Liang-Liang Fu et al. [104] | Production scheduling | Job splitting, Delivery time windows, Total setup cost, Transportation Cost | Mixed Integer Linear Programming | Metal Packaging Industry | France |
| Lu, C. et al. [184] | Flow Shop Scheduling | Setup time, Transportation time, Energy saving, Makespan | Backtracking search Algorithm | Industry | China |
| Pfund, M. E. et al. [221] | Deterministic Scheduling | Makespan, Number of late jobs, Total overtime, Average machine finishing time, Machine utilisation | Simulation model | Printed Wiring Board Manufacturer’s | USA |
| Seokgi Lee et al. [166] | Production Scheduling | Due dates, Total penalty costs, Earliness, tardiness, total energy consumption costs | Mixed integer Nonlinear prog. | Manufacturing | USA |
| Toksan, M.D. et al. [258] | Single machine Scheduling | Position-dependent fuzzy learning effect, Fuzzy Processing time, Makespan, Total completion time, Total weighted completion time | Mixed Integer Linear Programming | Manufacturing | Turkey |
| Wang, Y. et al. [276] | Multi-project scheduling | Activity duration, Schedule quality, Robustness, Risk level, Priority rule | Full Factorial Experiment | Manufacturing | China |
| Zhai, Y. et al. [297] | Dynamic Scheduling | Wind energy, Wind Speed, Electricity prices, Carbon footprint Working power, Job Processing time, Stand-by power | Time Series Models | Manufacturing | USA |

Table 2.12 Hybridisation approach-based scheduling

| Authors | Problem Type | Factors /Parameters | Approach | Sector | Country |
|---|---|---|---|---|---|
| Ishibuchi, H. et al. [131] | Flow Shop Scheduling | No. of Sampled Solutions, Average value of Probability function, Length of taboo list, Fuzzy due date | Simulated Annealing Taboo Search | General | Japan |
| Soon, T.H. et al. [122] | Simulation Based Scheduling | Lateness, Flow time, Tardiness, Resource utilization | Simulation technique, ANN | Manufacturing | Singapore |
| Tedford, J.D. et al. [254] | Production Scheduling | Difficulty, Run length, Priority, Machine performance, Machine reliability, Makespan, Flow time, Lateness, | Fuzzy logic Genetic Algorithm | Manufacturing | New Zealand |
| Asif Raza, S. et al. [229] | Maintenance Scheduling | Maintenance time, No. of Jobs, Continuous working time, Cost of Algorithm | Tabu Search Simulated Annealing | Manufacturing | Canada |
| Ballestin, F. & Leus, R. [27] | Single machine Scheduling | Stability, Job duration, Deviation between starting time | Three Metaheuristic algorithms | Manufacturing | Spain |
| Dhingra, A. et al. [80] | Flow shop scheduling | Set up time, No. of jobs, Total weighted tardiness, Total Weighted Earliness, Makespan | Hybrid Simulated Annealing | Manufacturing | India |
| Hsien-Chung Wu (2010) [283] | Single Machine Scheduling | Fuzzy earliness, Earliness, Tardiness, Fuzzy due date, Fuzzy processing time, Fuzzy completion time | Fuzzy logic Genetic Algorithm | Industry | Taiwan |
| Xiang gang, W. et al. [275] | Project Scheduling | Membership function, Resource cost, Capital cost, Activity duration, Simulation time, Population size | Fuzzy logic Genetic Algorithm | Manufacturing | China |
| Min Dai et al. [76] | Flexible Flow shop Scheduling | Makespan, Total energy consumption, Idle energy consumption, Energy consumption ratio | Genetic Simulated Annealing algorithm | Workshop | China |
| Huang, J. et al. [125] | Job shop scheduling | Dispatching Rule, Makespan, Average flow time, Maximal tardiness, and total tardiness. | Genetic Algorithm Fuzzy logic | Manufacturing | USA |
| Chaurasia, S.N. et al. [54] | Single Machine Scheduling | Release dates and sequence dependent setup times Population size, No. of optimal Solutions | Genetic Algorithm Evolutionary Algo. | Industry | India |
| Palacios, J. J. et al. [143] | Job Shop Scheduling | Fuzzy Makespan, Predictive Robustness | Fuzzy logic Tabu Search | Manufacturing | Spain |
| Liu, G.S. et al. [175] | Flow shop Scheduling | Energy consumption, Tardiness penalty, setup time, Tardiness, Processing times, Due dates | Fuzzy logic Genetic Algorithm | Tire industry (Automotive) | China |
| Mokhtari, H. et al. [200] | Flexible Job-Shop Scheduling | Total completion time, Total availability of system, Energy consumption | Genetic & Simulated Annealing Algorithm | Manufacturing | Iran |

| | | | | | |
|---|---|---|---|---|---|
| Wen, H. et al. [279] | Production Planning & Scheduling | Machine Processing time, Inventory cost, unit processing Time cost, Setting up cost, Over production penalty, Below production penalty | Simulation technique Neural network & Genetic algorithms | Manufacturing | China |
| Zandieh, M. et al. [295] | Job shop scheduling | Condition-based maintenance, Makespan, Total no. of Jobs, Total no. of machines, Total no. of Operations, Processing time | Imperialist Competitive Algo. Simulated Annealing | Industry | Iran |
| Gong, G. et al. [110] | Double flexible Job Shop scheduling | Processing time, Processing cost of workers, Energy consumption, Noise, Recycling of tool chip, Safety, Skill level of workers | Hybrid Genetic Algorithm | Manufacturing | China |

Table 2.13 Constraint based scheduling

| Authors | Problem Type | Factors /Parameters | Approach | Sector | Country | Constraint |
|---|---|---|---|---|---|---|
| Dubois, D. et al. [83] | Job Shop Scheduling | No. of Jobs, set of operations, Release date, Due date | Mathematical Model | Manufacturing | France | Fuzzy Constraints |
| Fortemps, P. [101] | Jobshop Scheduling | Makespan, Fuzzy duration, Centre of makespan, Spread of makespan | Fuzzy Approach | Industry | Belgium | Precedence |
| Oke, S.A. et al. [213] | Preventive Maintenance Scheduling | Cost of production of bolts and nuts, Cost of maintenance of Lathe machine, Cost of operation of lathe machine | Fuzzy logic | Manufacturing | Nigeria | Resource-constrained |
| Oke, S.A. et al. [212] | Preventive maintenance scheduling | Total preventive maintenance scheduling cost, Production cost | Mathematical Model | Shipping Industry | Nigeria | Resource-constrained |
| Allahverdi, A. [12] | Three Machine Flow-shop Scheduling | Makespan, Setup & Processing time, Set of Schedule | Computational Analysis | Manufacturing | Kuwait | Setup & Processing time |
| Muhuri, P.K. et al. [205] | Real-time task Scheduling | Fuzzy deadlines, Fuzzy processing times, Membership functions | Simulation experiments | Industry | India | Fuzzy timing constraints |
| Xianggang, W. et al. [275] | Project Scheduling | Membership function, Resource cost, Capital cost, Activity duration, Simulation time, Population size | Fuzzy logic Genetic Algorithm | Manufacturing | China | Resource-Constrained |
| Castro, P.M. et al. [42] | Multiproduct plant scheduling | Electricity Price, Power Availability, Due date, Production level | Mixed Integer linear Prog. | Manufacturing | Portugal | Energy |
| Vincent, T. [265] | Just-in-time Scheduling | No. of jobs, No. of machines, No. of sublots per operation, Number of indivisible elements, Release date, Due date | MCDM | Manufacturing | France | Lot-streaming constraint |
| Cesaret, B. et al. [43] | Single Machine Scheduling | Total Revenue, Sequence dependent Set up times, Release dates, Due dates, Tardiness | Tabu search | Manufacturing | Turkey | Production Capacity Order delivery |
| Artigues, C. et al. [18] | Energy Scheduling | Energy, Resource, Tardiness, Total time | Integer Programming | Industrial | France | Energy |
| Deming Lei et al. [167] | Job-shop Scheduling | Interval carbon footprint, Makespan, Uncertainty, Heterogeneous resources | Lexicographical Method | Manufacturing | China | Dual resource constrained |
| Fang Fu [103] | Project Scheduling | Inventory holding cost, Back-order cost | Mixed Integer | Construction | China | Resource |

| | | | | | | |
|---|---|---|---|---|---|---|
| Fang, K. et al. [92] | Flow shop scheduling | Makespan, Peak Power consumption, | Mixed Integer Prog. | Manufacturing | USA | Peak Power consumption |
| Knyazevaa, M. et al. [157] | Project Scheduling | Fuzzy numbers, computational time, Fuzzy plan, Fuzzy resource allocation, Heuristic priority rules | Fuzzy Logic | Industry | Russia | Resource |
| Bennell, J.A. et al. [31] | Dynamic Scheduling | Runway throughput, Earliness, Lateness, Cost of fuel, Flight time | Dynamic Programming | Aircraft Industry | UK | Time window constraints |
| Chia-Yu Hsu et al. [124] | Distributed Job Shop Scheduling | No. of Jobs, Makespan, Average flow time, Computation time, Average no. of unsatisfied Jobs | Fuzzy Constraint Directed Approach | Manufacturing | Taiwan | Set of Fuzzy constraint |
| Cheng, T.C.E. et al. [63] | Flow shop Scheduling | Makespan, Resource level, relocation problem | Johnson's algorithm | Manufacturing | Hong Kong | Resource Constrained |
| Devapriya, P. et al. [79] | Production Scheduling | Cost, Fleet size, Trucks' routes, Product lifetime, Travel time, Capacity of each truck | Mixed Integer Linear Prog. | Packaging Industry | USA | Planning horizon constraint |
| Seokgi Lee et al. [166] | Production Scheduling | Due dates, Total penalty costs, Earliness, tardiness, total energy consumption costs | Mixed integer Nonlinear Prog. | Manufacturing | USA | Energy |

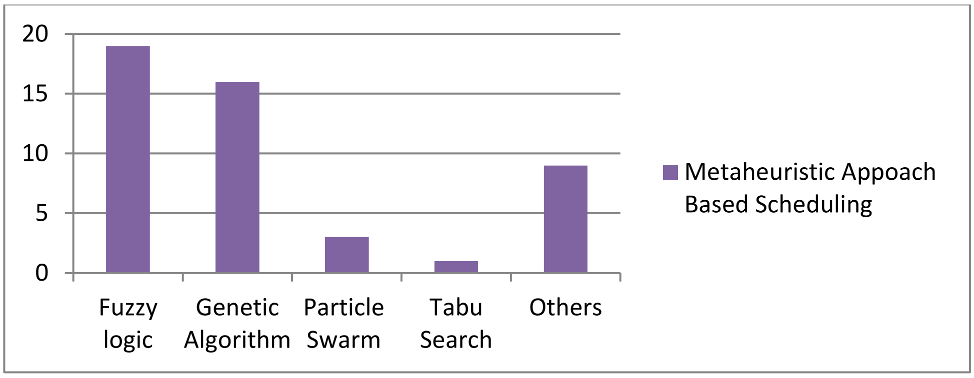


Fig. 2.8 Metaheuristic approaches-based scheduling (Total 48 Papers)

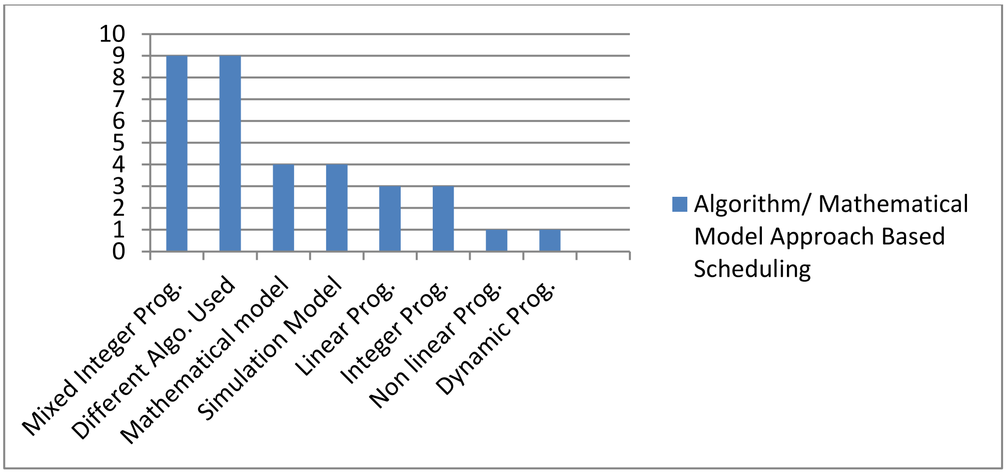


Fig. 2.9 Algorithm/ Mathematical model approach-based scheduling (Total 51 Papers)

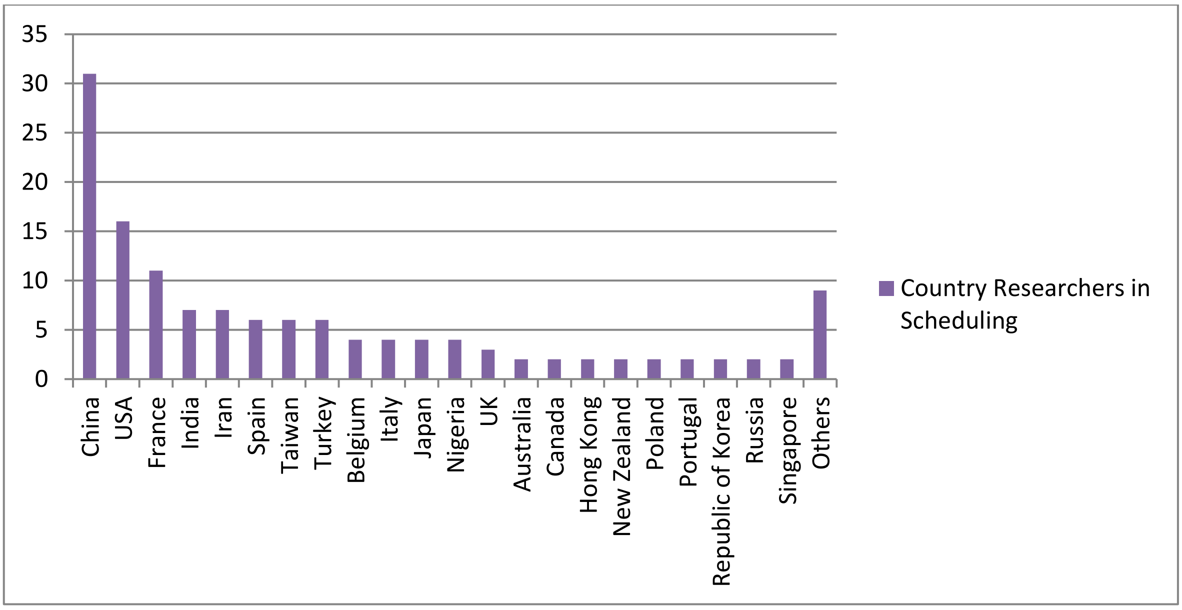


Fig. 2.10 Country researchers in scheduling (Total 136 Papers)

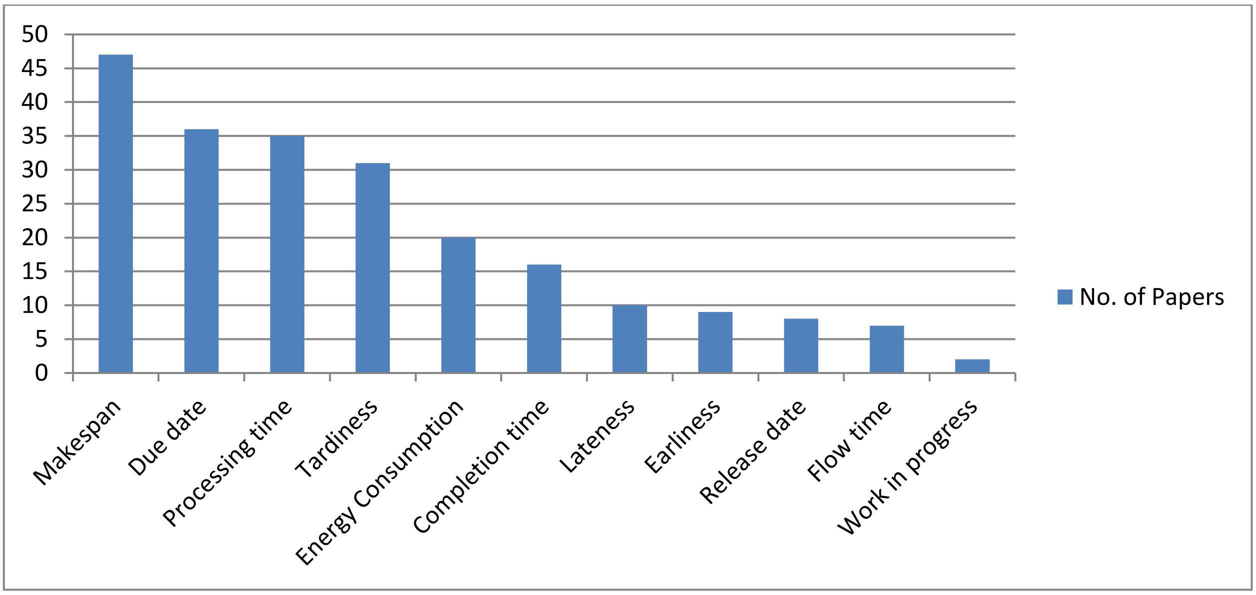


Fig. 2.11 Most important parameters in scheduling (136 papers)

Table 2.14 Identified research gaps with their research objectives

| Identified research Gaps | Research objectives taken for fulfilling the research gaps |
|---|---|
| Material selection of automotive part manufacturing is also identified as new area of research identified from the literature review. | To find out the best material for automotive part manufacturing |
| Prioritization of maintenance task on industrial equipment, prioritization of jobs in FMS are touched areas of research but Prioritization of PDC Automotive parts using various dispatching rule is new area of research. | Prioritize the automotive parts for production operations using various dispatching rules and to minimize the scheduling parameters such mean flow time, weighted mean flow time and maximum lateness etc |
| Scheduling work like production scheduling in ERP System, scheduling of FMS system, energy efficient scheduling in bottle industry are covered area of research but scheduling of Automotive parts manufacturing is untouched area of research. | To develop energy efficient scheduling system for automotive part manufacturing and to find out the best feasible routes of machining these parts. |
| No previous study is found related to modelling and simulation of automotive part manufacturing. | To develop a simulation model for automotive part manufacturing |
| No case study is found on prioritizing scheduling parameters of automotive part manufacturing in Indian automotive industry. | To identify and prioritize the scheduling parameters in the automotive industry |

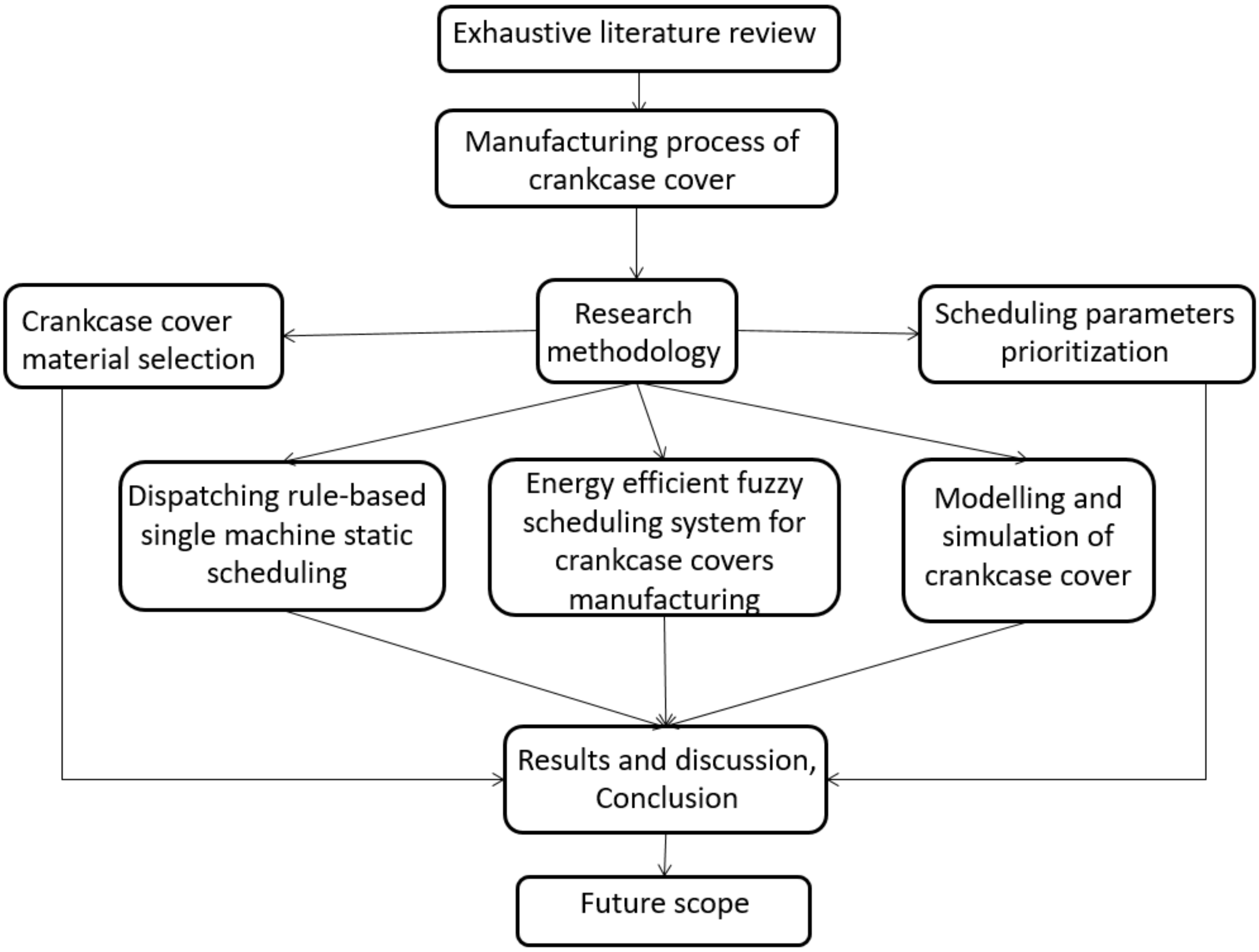


Fig. 2.12 Flowchart of research work

# Chapter-3

# RESEARCH METHODOLOGY

## 3.1 Material selection methodology

Material Selection Methodology includes the MCDM methods and optimization methods. MCDM method is stratified into two types, MADM and fuzzy MCDM methods. Multiple objective decision making, mathematical programming, computer simulation, and genetic algorithm come in the category of optimization methods [134]. The stratification of material selection methods is shown in Fig. 3.1.

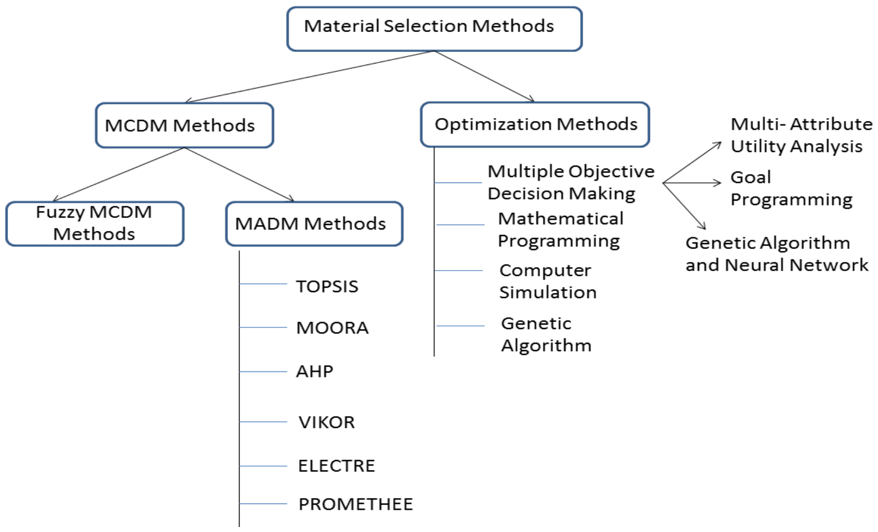


Fig. 3.1 Stratification of material selection methods [134]

### *3.1.1 TOPSIS methodology*

TOPSIS methodology was proposed by Tzeng and Huang in 1981. TOPSIS is an MCDM tool generally used in combination with MOORA, AHP, ELECTRE, or PROMETHEE. The advantage offered by this technique is that it allows a tradeoff between the criteria where a bad result by one criteria is compensated by a good result by other criteria [211]. TOPSIS is a simple approach and it is superior to other MCDM techniques for the material selection problems because it handles qualitative as well as quantitative information [129].

For the proper material selection of crankcase cover, we must compare the attributes or properties of these crankcase cover. The seven attributes taken for this study are Brinell hardness, yield strength, % elongation, ultimate tensile strength, young’s modulus, fatigue strength, and material cost. The Six alternatives are taken which are commonly used in the industries are Alloy 360, Alloy 380, Alloy A380, Alloy 383, Alloy B390, and Alloy 13. These material selection criteria are shown in Fig. 3.2.

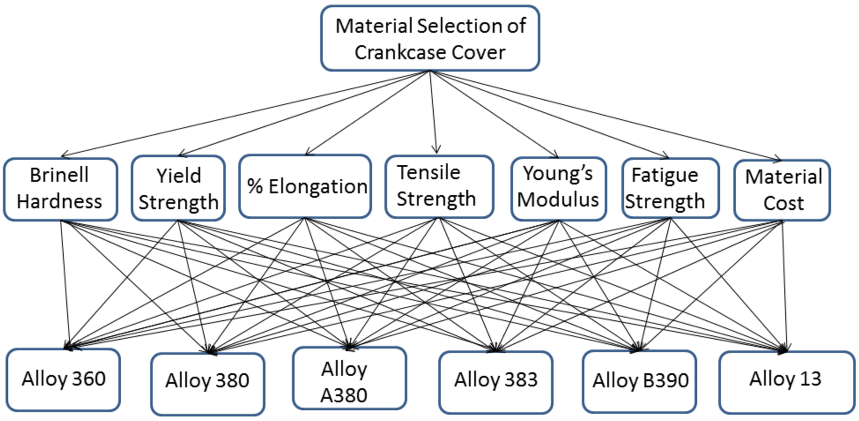


Fig. 3.2 Material selection criteria of TOPSIS

MCDM methods helps in identifying the best alternative based on different criteria. TOPSIS is one of the best methods of MCDM in dealing with real-life problems [292]. The steps of TOPSIS methodology are as follows:

Step 1 The first step is to construct a Decision Matrix based on different alternatives and criteria.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & \cdots & x_{mn} \end{bmatrix} \qquad (1)$$

Where i = alternative index (1, 2, 3…m) and j=criterion index (j = 1, 2, 3…n) in Eq. (1).

Step 2 Find the normalized decision matrix $(R_{ij})$ using Eq. (2).

$$R_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \qquad (2)$$

Step 3 Calculate the weighted decision matrix $d_{ij}$using Eq. (3)

$$d_{ij} = w_j \times R_{ij} \qquad (3)$$

Step 4 Find the positive ideal solution $A^+$and negative ideal solution $A^-$.

$$A^+ = \{d_1^+, d_2^+ \ldots, d_n^+\}, where: d_j^+ = \{(max\, i\,(d_{ij}) if j \in K); (min\, i\,(d_{ij}) if j \in K')\} \qquad (4)$$

$$A^- = \{d_1^-, d_2^- \ldots., d_n^-\}, where: d_j^- = \{(min\, i\,(d_{ij}) if j \in K); (max\, i\,(d_{ij}) if j \in K')\} \quad (5)$$

Where, K and K' are beneficial and the non-beneficial based attributes in Eq. (4-5) [272].

Step 5 Calculate the separation distances ($S^+$ & $S^-$) of each alternative from ideal and non-ideal solution using Eq. (6) and Eq. (7).

$$S^+ = \sqrt{\sum_{j=1}^{n} (d_j^+ - d_{ij})^2} \quad (6)$$

$$S^- = \sqrt{\sum_{j=1}^{n} (d_j^- - d_{ij})^2} \quad (7)$$

Step 6 Measure the relative closeness$C_i$ values using the Eq. (8)

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-}, 0 \leq C_i \leq 1 \quad (8)$$

Step 7 Based on the relative closeness values, ranking of alternatives is obtained.

### *3.1.2 MOORA methodology*

MOORA methodology is a multi-objective optimization technique which is preferred than other MCDM approach because of its fast computational time. MOORA methodology consists of two components. The first one is the ration system developed in 2004 by Brauers and the other in reference point approach developed in 2006 by Brauers and Zavadskas. This technique is used in solving various complex decision-making problems [38, 45]. This technique can optimize the two or more conflicting criteria at the same time e.g. minimize cost and maximize profit [146]. The methodology of MOORA is as follows:

Step 1 Find the decision matrix $X$ in which $x_{ij}$ shows performance index of $i_{th}$ alternative w.r.t $j_{th}$ attribute, i = 1, 2, …, m and j = 1, 2, …, n in Eq. (9).

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & \cdots & x_{mn} \end{bmatrix} \quad (9)$$

Step 2 Find normalized decision matrix $x_{ij}^*$using Eq. (10)

$$x_{ij}^* = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, 0 < x_{ij}^* < 1 \tag{10}$$

Step 3 The overall performance score of each alternative $y_i^*$ is calculated by adding all beneficial criteria and subtracting the non- beneficial criteria as given in Eq. (11).

$$y_i^* = \sum_{j=1}^{q} x_{ij}^* - \sum_{j=q+1}^{n} x_{ij}^* \tag{11}$$

Here, q and (n - q) are the number of beneficial and non-beneficial criteria respectively. Eq.(12) can be used for giving weights to the different criteria [45, 146].

$$y_i^* = \sum_{j=1}^{q} w_j x_{ij}^* - \sum_{j=q+1}^{n} w_j x_{ij}^* \tag{12}$$

Step 4 The ranking of alternatives is obtained using $y_i^*$ values from Eq. (11) and Eq. (12).
These above four steps show the calculation of the ration system part of MOORA method. The reference point part is shown in step 5 and 6.
Step 5 Determine the Tchebycheff Min–Max metric [39]

$$\min_i \{ \max_j \left| s_j - x_{ij}^* \right| \} \tag{13}$$

$s_j$ is the $j_{th}$ coordinate of the reference point which shows those alternatives having most desirable performances with respect to $j_{th}$ criterion. For determining $s_j$, Eq. (14) may be used. Eq. (15) can be used in case of assigning weightages to alternatives.

$$s_j \begin{cases} \max_i x_{ij}^* \\ \min_i x_{ij}^* \end{cases}, \tag{14}$$

$\max x_{ij}^*$ represents beneficial criteria & $min\, x_{ij}^*$ represents non-beneficial criteria.

$$\min_i \{ \max_j \left| w_j s_j - w_j x_{ij}^* \right| \} \tag{15}$$

Step 6 Finally, selection of alternatives is done using the minimum deviation value from reference point [146].

### *3.1.3 PROMETHEE methodology*

PROMETHEE is an MCDM method developed by Brans et al. [36, 37]. PROMETHEE methodology is classified into two types PROMETHEE I and PROMETHEE II. PROMETHEE I is used for obtaining the partial ranking of alternatives whereas PROMETHEE II provides the full ranking of alternatives.

The aggregated preference index of ‘a’ over ‘b’ is represented by $\pi(a,b)$ for each alternative a, belonging to the set A of alternatives. The leaving flow $\phi^{+}(a)$ and the entering flow$\phi^{-}(a)$ show the positive and negative dominancy of alternative ‘a’ on all another alternative.

The methodology of PROMETHEE II is described as follows.

Step 1 Normalize the evaluation matrix or decision matrix ($R_{ij}$)

$$R_{ij} = \frac{[x_{ij} - \min(x_{ij})]}{[\max(x_{ij}) - \min(x_{ij})]} \tag{16}$$

$$R_{ij} = \frac{[\max(x_{ij}) - x_{ij}]}{[\max(x_{ij}) - \min(x_{ij})]} \tag{17}$$

Where, i=1, 2, …, m; j=1, 2,…, n. Eq. (16) and Eq. (17) are applicable for beneficial and non-beneficial criteria respectively.

Step 2 Calculate the evaluative differences of $i^{th}$ alternative with respect to another alternative

Step 3 Calculate the preference function $P_j(s,t)$ using Eq. (18) and Eq. (19).

$$P_j(s,t) = 0 \quad \text{if } R_{sj} \leq R_{tj} \tag{18}$$

$$P_j(s,t) = \left(R_{sj} - R_{tj}\right) \quad \text{if} R_{sj} > R_{tj} \tag{19}$$

Step 4 Determine the aggregated preference function $\pi(s,t)$

$$\pi(s,t) = \left[\frac{\sum_{j=1}^{n} W_j P_j(s,t)}{\sum_{j=1}^{n} W_j}\right] \tag{20}$$

Step 5 Calculate the leaving and the entering outranking flows

Leaving flow for $s^{th}$ alternative

$$\phi^{+} = \frac{1}{m-1}\sum_{t=1}^{m} \pi(s,t)\ (s \neq t) \tag{21}$$

Entering flow for $s^{th}$ alternative

$$\varphi^{-} = \frac{1}{m-1}\sum_{t=1}^{m} \pi(t,s)\ (s \neq t) \tag{22}$$

Where, m is number of alternatives in Eq. (21) and Eq. (22)

Step 6 Calculate the net outranking flow $\phi(s)$ for each alternative

$$\phi(s) = \phi^{+}(s) - \phi^{-}(s) \tag{23}$$

Step 7 Determine the ranking of alternatives based on the net outranking flow value $\phi(a)$.

## 3.2 Fuzzy methodology

The concept of fuzzy logic was developed by Lotfi Zadeh in 1965. This approach can process data by providing a piece of incomplete and uncertain information rather than crisp information [260]. Most of the control system uses a fuzzy logic control-based methodology. Fuzzy rules used in these systems hold the performance data [256].

Steps in the fuzzy methodology are shown as a flowchart in Fig. 3.3. Step 1 includes the selection of input and output variables. Step 2 consists of the selection of membership functions for these variables. Step 3 includes the development of a linguistic rule base based on the performance data gathered from the various experts. Step 4 includes the defuzzification process in which linguistic variables are converted into the crisp form.

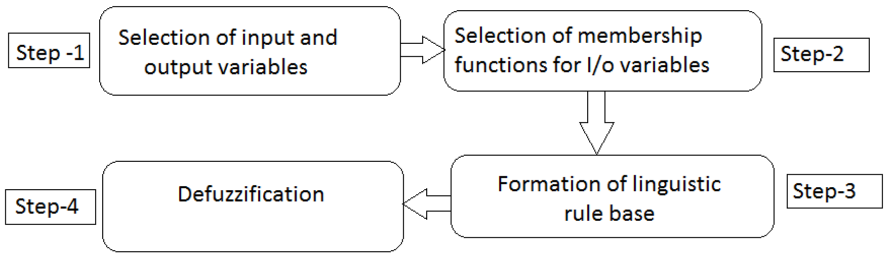


Fig. 3.3 Flowchart of steps in the fuzzy methodology

Route selection can be done in two ways in the fuzzy logic system. These two ways are the fuzzy set approach and the fuzzy logic system in MATLAB.

### *3.2.1 Fuzzy set approach*

The route can be optimized by minimizing several factors. These factors are travel time, work in queue, total processing time, energy consumption, number of processing steps and number of machines blocked [47].

Among these factors, we have used only four factors (travel time, work in queue, total processing time, and energy consumption) in our study. This factor's contributions in terms of membership function are defined in Eq. (24) to Eq. (27). A membership function $u_1(i)$ for the minimization of the total processing time (goal 1) is defined by Eq. (24).

$$u_1(i) = \frac{(\mathrm{TPT_b} - \mathrm{TPT_i})}{(\mathrm{TPT_b} - \mathrm{TPT_a})} \tag{24}$$

Where $TPT_i$ = total processing time required for routing i, $TPT_b - TPT_a$represents the difference between the maximum and minimum total processing time. Similarly, the membership functions for the minimization of total work in queue (goal 2), total travel time (goal 3), and total energy consumption (goal 4) are defined by Eq. (25), Eq. (26), and

Eq. (27) respectively. The formula for the calculation of the final membership function $u_a(i)$ is given in Eq. (28).

$$\mathrm{u_2(i)} = \frac{(\mathrm{TWIQ_b} - \mathrm{TWIQ_i})}{\mathrm{TWIQ_b}} \tag{25}$$

$$\mathrm{u_3(i)} = \frac{(\mathrm{TTT_b} - \mathrm{TTT_i})}{(\mathrm{TTT_b} - \mathrm{TTT_a})} \tag{26}$$

$$\mathrm{u_4(i)} = \frac{(\mathrm{TEC_b} - \mathrm{TEC_i})}{(\mathrm{TEC_b} - \mathrm{TEC_a})} \tag{27}$$

$$\mathrm{u_a(i)} = \sum_{j=1}^{n} \left[ \frac{\mathrm{w_j}}{\sum_{j=1}^{n} \mathrm{w_j}} \times \mathrm{u_j(i)} \right] \tag{28}$$

Where, $\mathrm{u_j(i)}$ = membership of routing i to goal j and $\mathrm{w_j}$= weight of goal j.

*3.2.2 Fuzzy logic system in MATLAB*

Fuzzy logic gives the best results in case of uncertainty and any missing information. This technique can be effectively applied to all control problems [240]. The structure of the fuzzy logic system consists of a fuzzifier, defuzzifier, rule base, and an inference engine. Fuzzifier converts the crisp input into fuzzy input. The inference engine utilized the rule base to convert fuzzy input into a fuzzy output. Defuzzifier converts the fuzzy output into crisp output. The Structure of the fuzzy logic system is shown in Fig. 3.4 [117].

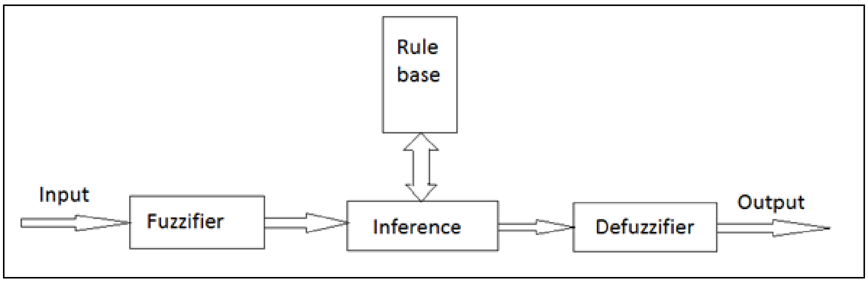


Fig. 3.4 Structure of fuzzy logic system [117]

## 3.3 Fuzzy TOPSIS method for prioritizing scheduling parameters

The basic methodology includes the following steps.

*3.3.1 Fuzzy Set theory*

This theory is based on the fuzzy set characterized by the membership function that lies between zero and one and deals with uncertainty, vagueness, and partial information [293]. A triangular fuzzy number is denoted as the triplet $\mathrm{s} = [\mathrm{s^L}, \mathrm{s^M}, \mathrm{s^R}]$. The membership function of any triangular fuzzy number is represented by $\mu_s(x)$; each element x belongs to the universe of discourse X. This membership function $\mu_s(x)$ is expressed in Eq. (29).

$$\mu_s(x) = \begin{cases} 0 & x < s^L \\ \dfrac{x - s^L}{s^m - s^L} & s^L \le x \le s^M \\ \dfrac{s^R - x}{s^R - s^m} & s^M \le x \le s^R \\ 0 & x > s^R \end{cases} \tag{29}$$

Where, $s^L, s^M, s^R$ are crisp numbers.

*3.3.2 Fuzzy TOPSIS method*

TOPSIS technique was the first time applied in the fuzzy environment for the group decision making in 1997 by Chen –Tung Chen. In fuzzy TOPSIS methodology, the linguistic variable is used with a fuzzy number on a point scale [57]. The flowchart of this methodology is shown in Fig. 3.5. The methodology is shown as follows:

Step 1 Fuzzy TOPSIS starts with the establishment of a committee of decision-makers.

Step 2 Define Linguistic Variable terms with their Fuzzy Number on the point scale. This scale is defined in Table 3.1 using the linguistic terms which are negative low (NLO), low (LO), average or arithmetic mean (AM), high (HI), and positive high (PHI).

Table 3.1 Linguistic variable terms with their fuzzy number

| Linguistic term | Fuzzy number |
|---|---|
| Negative low (NLO) | 1,1,3 |
| Low (LO) | 1,3,5 |
| Average (AM) | 3,5,7 |
| High (HI) | 5,7,9 |
| Positive high (PHI) | 7,9,9 |

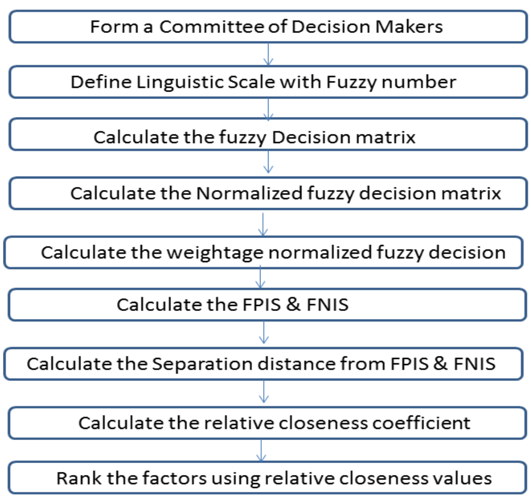


Fig. 3.5 Flowchart of fuzzy TOPSIS methodology

Step 3 Find the decision matrix (DM) $x_{ij}, x_{ij} = (a_{ij}, b_{ij}, c_{ij})$ which is a fuzzy number with $i = 1,2, \ldots, n$ number of decision maker of various automobile companies and $j = 1,2, \ldots, n$ number of scheduling parameters.

$$DM = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{in} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix} \tag{30}$$

Step 4 Find the Normalized fuzzy decision matrix $R_{ij}$

Eq. (31) is showing a normalized decision matrix for non-beneficial criteria. For beneficial criteria, larger $R_{ij}$ is desirable, whereas, for cost criteria, smaller $R_{ij}$ is desirable.

$$NDM = [R_{ij}]_{m \times n}, \quad R_{ij} = \left( \frac{c_j^*}{c_{ij}}, \frac{c_j^*}{b_{ij}}, \frac{c_j^*}{a_{ij}} \right) \tag{31}$$

Where, $c_j^* = \min_i c$

Step 5 Determine the weightage normalized fuzzy decision matrix V

This matrix V is obtained by multiplying the weightage $w_j$ given to the decision makers with matrix $R_{ij}$.

$$V = v_{ij} = w_j \times R_{ij} \tag{32}$$

Step 6 Calculate the Fuzzy positive ideal solution (FPIS) $A^+$ and Fuzzy negative ideal solution (FNIS) $A^-$.

$$A^+ = \{v_1^+, v_2^+ \ldots, v_n^+\} \tag{33}$$

$$A^- = \{v_1^-, v_2^- \ldots, v_n^-\} \tag{34}$$

Step 7 Calculate the $s_i^+$ separation from the $A^+$ and $s_i^-$ separation from the $A^-$.

$$s_i^+ = \sqrt{\sum_{j=1}^{n} (v_j^+ - v_{ij})^2} \qquad i = 1,2, \ldots, m \tag{35}$$

$$s_i^- = \sqrt{\sum_{j=1}^{n} (v_j^- - v_{ij})^2} \qquad i = 1,2, \ldots, m \tag{36}$$

Step 8 Calculate the relative closeness coefficient $C_j$

$$C_j = \frac{s_i^+}{s_i^+ + s_i^-} \tag{37}$$

$C_j = 1$ if $A_i = A^+, C_j = 0$ if $A_i = A^-$, $s_i^- \geq 0$ and $s_i^+ \geq 0$, then clearly $0 \leq C_j \leq 1$.

Step 9 The ranking of alternatives is obtained using relative closeness values.

### 3.4 DEMATEL methodology

DEMATEL methodology is based on the causal relationship and provides visual graphical relations between the complex criteria. This method also identifies the cause and effect groups among the various criteria [1]. It is the only method that provides visualization to researchers about interrelations among criteria. For providing visualization, it uses the basics of graph theory [127]. The flowchart of the DEMATEL methodology is shown in Fig. 3.6.

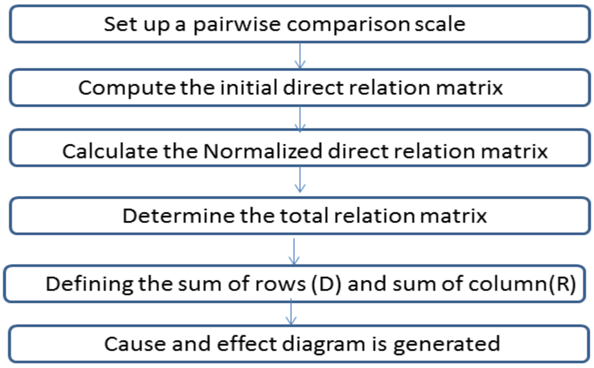


Fig. 3.6 Flowchart of DEMATEL methodology

The steps involved within the DEMATEL methodology are as follows.

Step 1 Set up a pairwise comparison scale of the DEMATEL method

Table 3.2 shows the comparison scale includes the terms which are represented by the numerical.

Table 3.2 Comparison Scale

| Terms | Numerical |
|---|---|
| No effect | 0 |
| Low effect | 1 |
| Medium effect | 2 |
| High effect | 3 |
| Very high effect | 4 |

Step 2 Compute the initial direct relation matrix M

This matrix M is a $n \times n$ matrix generated from a comparison scale in terms of numerical and it shows the influences of all criteria on each other. M is a square matrix in which diagonal elements $m_{ii}$ is zero.

$$M = \begin{bmatrix} 0 & m_{12} & \cdots & m_{1n} \\ m_{21} & 0 & 0 & m_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ m_{n1} & m_{n2} & \cdots & 0 \end{bmatrix} \tag{38}$$

Step 3 Calculate the Normalized direct relation matrix U i.e., $U = [U_{ij}]_{n\times n}$ and $0 \le U_{ij} \le 1$. This matrix can be determined from the Eq. (39) and Eq. (40). Set of elements contains in a system is $S = \{s_1, s_2, \ldots, s_n\}$ .

$$S = \frac{1}{\max_{1\le i\le n} \sum_{j=1}^{n} x_{ij}} \tag{39}$$

$$U = S \times M \tag{40}$$

Step 4 Determine the total relation matrix V using Eq. (41) and Eq. (42) in which identity matrix is denoted by $I$.

$$V = M + M^2 + \cdots + M^h = M(I - M^h)(I - M)^{-1} \tag{41}$$

when $\lim_{h\to\infty} M^h = [0]_{n\times n}$,

$$V = (v_{ij})_{n\times n} = M(I - M)^{-1} \tag{42}$$

Step 5 Defining the sum of rows (D) and sum of column (R) in the total relation matrix $V$as vector d and r through Eq. (43) and Eq. (44).

$$D = (d_i)_{n\times 1} = \left[\sum_{j=1}^{n} v_{ij}\right]_{n\times 1} \tag{43}$$

$$R = (r_i)_{1\times n} = \left[\sum_{i=}^{n} v_{ij}\right]_{1\times n} \tag{44}$$

Step 6 With the help of Eq. (43) and Eq. (44), cause and effect diagram is generated to find the most affected criteria/parameter.

# Chapter-4

# Case Study-1

**Integrated TOPSIS-PROMETHEE-MOORA model for material selection of crankcase cover**

Material selection is an important task for designers in all industries. To satisfy customer needs, designers must predict the performance of all available materials and find out the best material for the product. Since the various materials are available in the market with diverse characteristics, which makes the material selection process complex. So, there is an indispensable need for a proper material selection methodology. The designers must identify the best approach which enhanced the product performance and reduced the time of designing. In this study, the first-time selection of materials for a two-wheeler crankcase cover is done using the integrated TOPSIS PROMETHEE and MOORA model. The final rankings of alternatives obtained from this novel proposed model are also compared with each other for finding the best material for crankcase cover. Six aluminum alloys (Alloy 360, Alloy 380, Alloy A380, Alloy 383, Alloy B390, and Alloy 13) are taken as alternatives, and seven attributes (Brinell hardness, yield strength, % elongation, young's modulus, ultimate tensile strength, fatigue strength, and material cost) are taken as criteria for this study.

## 4.1 Application of TOPSIS-PROMETHEE-MOORA model

In this study, seven attributes are considered, and these attributes are of different types, among these six attributes belong to the category of beneficial criteria and there are only one non- beneficial criteria. The beneficial criteria are brinell hardness, yield strength, % elongation, tensile strength, young's modulus, and fatigue strength whereas the material cost is the non-beneficial criteria. Our aim of this study is to maximize the beneficial criteria and minimize the non-beneficial criteria. The conflicting criteria are optimized using the Integrated TOPSIS MOORA approach. Table 4.1 represents the symbol for these conflicting criterions and Table 4.2 shows all symbols used for different alternatives. The Specification parameter values of various aluminum alloys as collected from the literature review are shown in Table 4.3. This entire numerical value used in Table 4.3 is converted to an approximate score out of 10 as shown in Table 4.4.

Table 4.1 Crankcase cover material selection criteria

| Attributes of Crankcase Cover | Symbol |
|---|---|
| Brinell Hardness (HB) | $C_1$ |
| Yield Strength (MPa) | $C_2$ |
| Elongation [% (in 2 inches)] | $C_3$ |
| Tensile Strength (MPa) | $C_4$ |
| Young' Modulus (GPa) | $C_5$ |
| Fatigue Strength (MPa) | $C_6$ |
| Crankcase Cover Material Cost (US $ per ton) | $C_7$ |

Table 4.2 Crankcase cover material alternatives

| Crankcase cover materials | Symbol |
|---|---|
| Aluminum Alloy 360 | $A_1$ |
| Aluminum Alloy 380 | $A_2$ |
| Aluminum Alloy A380 | $A_3$ |
| Aluminum Alloy 383 | $A_4$ |
| Aluminum Alloy B390 | $A_5$ |
| Aluminum Alloy 13 | $A_6$ |

Table 4.3 Specification parameter of various aluminum alloys

| Sl. No. | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ |
|---|---|---|---|---|---|---|---|
| $A_1$ | 75 | 172 | 2.5 | 303 | 71 | 138 | 1490.52 |
| $A_2$ | 80 | 159 | 3.5 | 317 | 71 | 138 | 1478.20 |
| $A_3$ | 80 | 159 | 3.5 | 324 | 71 | 138 | 1355.02 |
| $A_4$ | 75 | 152 | 3.5 | 310 | 71 | 145 | 1478.20 |
| $A_5$ | 120 | 248 | <1 | 317 | 81 | 138 | 1724.57 |
| $A_6$ | 80 | 145 | 2.5 | 296 | 71 | 131 | 1847.75 |

## 4.2 Calculation using TOPSIS-MOORA model

Weighted normalized decision matrix using TOPSIS and MOORA model is represented in Table 4.5.

Table 4.4 Decision matrix for crankcase cover material selection

| Sl. No. | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ |
|---|---|---|---|---|---|---|---|
| $A_1$ | 6.00 | 6.88 | 6.25 | 9.18 | 8.66 | 9.20 | 7.84 |
| $A_2$ | 6.40 | 6.36 | 8.75 | 9.61 | 8.66 | 9.20 | 7.78 |
| $A_3$ | 6.40 | 6.36 | 8.75 | 9.82 | 8.66 | 9.20 | 7.13 |
| $A_4$ | 6.00 | 6.08 | 8.75 | 9.39 | 8.66 | 9.67 | 7.78 |
| $A_5$ | 9.60 | 9.92 | 2.00 | 9.61 | 9.88 | 9.20 | 9.08 |
| $A_6$ | 6.40 | 5.80 | 6.25 | 8.97 | 8.66 | 8.73 | 9.73 |

Table 4.5 Weighted normalized decision matrix using TOPSIS and MOORA model

| Sl. No. | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ |
|---|---|---|---|---|---|---|---|
| $A_1$ | 0.354 | 0.399 | 0.354 | 0.397 | 0.398 | 0.408 | 0.387 |
| $A_2$ | 0.378 | 0.369 | 0.495 | 0.416 | 0.398 | 0.408 | 0.384 |
| $A_3$ | 0.378 | 0.369 | 0.495 | 0.425 | 0.398 | 0.408 | 0.352 |
| $A_4$ | 0.354 | 0.353 | 0.495 | 0.406 | 0.398 | 0.429 | 0.384 |
| $A_5$ | 0.567 | 0.575 | 0.113 | 0.416 | 0.454 | 0.408 | 0.448 |
| $A_6$ | 0.378 | 0.336 | 0.354 | 0.388 | 0.398 | 0.387 | 0.480 |

## 4.3 Calculation using PROMETHEE model

In the PROMETHEE model, the ranking of material selection is done based on the aggregate preference function. The calculation of the aggregate preference function is depicted in Table 4.7.

Table 4.6 Normalized decision matrix using PROMETHEE

| Sl. No. | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ |
|---|---|---|---|---|---|---|---|
| $A_1$ | 0.000 | 0.262 | 0.615 | 0.250 | 0.000 | 0.500 | 0.725 |
| $A_2$ | 0.111 | 0.136 | 1.000 | 0.750 | 0.000 | 0.500 | 0.750 |
| $A_3$ | 0.111 | 0.136 | 1.000 | 1.000 | 0.000 | 0.500 | 1.000 |
| $A_4$ | 0.000 | 0.068 | 1.000 | 0.500 | 0.000 | 1.000 | 0.750 |
| $A_5$ | 1.000 | 1.000 | 0.000 | 0.750 | 1.000 | 0.500 | 0.250 |
| $A_6$ | 0.111 | 0.000 | 0.615 | 0.000 | 0.000 | 0.000 | 0.000 |

Table 4.7 Calculation of aggregate preference function

| Alternatives | $A_1$ | $A_2$ | $A_3$ | $A_4$ | $A_5$ | $A_6$ |
|---|---|---|---|---|---|---|
| $A_1$ | 0.000 | 0.126 | 0.126 | 0.194 | 1.090 | 1.537 |
| $A_2$ | 1.021 | 0.000 | 0.000 | 0.429 | 1.500 | 2.521 |
| $A_3$ | 1.521 | 0.500 | 0.000 | 0.929 | 2.000 | 3.021 |
| $A_4$ | 1.160 | 0.500 | 0.500 | 0.000 | 2.000 | 2.703 |
| $A_5$ | 3.238 | 2.753 | 2.753 | 3.182 | 0.000 | 4.389 |
| $A_6$ | 0.111 | 0.000 | 0.000 | 0.111 | 0.615 | 0.000 |

# Chapter-5

# Case Study-2

## Dispatching rule-based single machine static scheduling of crankcase covers

The research focuses on the multi-objective single machine static scheduling problems of motorcycle crankcase cover. To solve these static scheduling problems, dispatching rules are used. Various dispatching rules used in this study are the EDD, SPT, CR, LPT, WSPT, COVERT, and Hodgson's algorithm. The objective of the paper is to sequence the different crankcase covers and to minimizes average flow time, an average hour early, and an average hour past due, etc. This study helps us to obtain optimal job prioritization of two-wheeler crankcase covers in the automobile industry. Results show that shifting the production system from WSPT approach scheduling to the EDD scheduling approach, it minimizes the mean flow time by 2.75%, weighted mean flow time by 27.91%, and maximum lateness by 21.87%. This research is very useful for all automotive industries as well as research organizations.

## 5.1 Problem definition and formulation

We have taken four types of crankcases covers in our study. Our main aim is to do single machine scheduling of this crankcase cover on the vertical milling center. These parts are cover left side crankcase KWPG, cover left crankcase K38, cover crankcase 206 G, and cover right crankcase KTE as shown in Fig. 5.1 to Fig. 5.4.

Fig. 5.1 Cover left side crankcase KWPG

Fig. 5.2 Cover left crankcase K38

Fig. 5.3 Cover crankcase 206 G Fig. 5.4 Cover right crankcase KTE

*5.1.1 Nomenclature*

$P_j$= Total Processing time of job j including setup time (hrs)
$T_j$= Time duration of job j since Order arrived (hrs)
S = Part lot Sequence
$T_b$= Begin work time (hrs)
$T_{fi}$= Finish time for lot (hrs)
$T_{fl}$= Flow time for lot (hrs)
$T_d$= Time duration until the due date (hrs)
$T_s$= Slack time remaining (hrs)
$T_{sp}$= Scheduled customer pickup time
$T_{ap}$= Actual customer pickup time
$T_{he}$= hours early
$T_{hpd}$= hours past due
Some data is collected from the industry, and some are taken from the literature review and industry experts. Table 5.1 shows the data of different parts.

Table 5.1 Data table of different parts

| Part lot | $T_j$ | $P_j$ | $T_d$ |
|---|---|---|---|
| K38 | 2 | 3.5 | 7 |
| 206 G | 1 | 2 | 9 |
| KTE | 7 | 4 | 20 |
| KWPG | 9 | 6 | 28 |

**5.2 EDD Approach**

For ‘n’ jobs on a single machine, we have different priority rules FCFS, SPT, EDD, STR, and CR. EDD priority rule sequences the jobs by their due dates. This rule also minimizes the maximum lateness and maximum tardiness [255]. The calculations regarding the sequence of operations using the earliest due date approach are represented in Table 5.2.

Table 5.2 Sequence of operations using earliest due date approach

| $S$ | $T_j$ | $T_b$ | $P_j$ | $T_{fi}$ | $T_{fl}$ | $T_{sp}$ | $T_{ap}$ | $T_{he}$ | $T_{hpd}$ |
|---|---|---|---|---|---|---|---|---|---|
| K38 | 2 | 0 | 3.5 | 3.5 | 5.5 | 7 | 10 | 6.5 | 3 |
| 206 G | 1 | 3.5 | 2 | 5.5 | 6.5 | 9 | 12 | 6.5 | 3 |
| KTE | 7 | 5.5 | 4 | 9.5 | 16.5 | 20 | 23 | 13.5 | 3 |
| KWPG | 9 | 9.5 | 6 | 15.5 | 24.5 | 28 | 30 | 14.5 | 2 |

Mean flow time = 13.25 hrs

Weighted mean flow time = 10.87 hrs

Average in-process inventory = 2.19 jobs

Mean lateness = 7.5 hrs

No. of tardy jobs = 0

Maximum lateness = 12.5 hrs

### 5.3 SPT Approach

SPT rule helps in minimizing the mean flow time, total waiting time, maximum waiting time, and total completion time, etc. It also maximizes shop floor utilization. This rule also provides the lowest mean finish time for a single workstation problem. But it increases total inventory because it finishes all work very fast compared to other rules. The calculations regarding the sequence of operations using the shortest processing time approach are represented in Table 5.3.

Table 5.3 Sequence of operations using shortest processing time approach

| $S$ | $T_j$ | $T_b$ | $P_j$ | $T_{fi}$ | $T_{fl}$ | $T_{sp}$ | $T_{ap}$ | $T_{he}$ | $T_{hpd}$ |
|---|---|---|---|---|---|---|---|---|---|
| 206 G | 1 | 0 | 2 | 2 | 3 | 9 | 10 | 8 | 1 |
| K 38 | 2 | 2 | 3.5 | 5.5 | 7.5 | 7 | 12 | 6.5 | 5 |
| KTE | 7 | 5.5 | 4 | 9.5 | 16.5 | 20 | 25 | 15.5 | 5 |
| KWPG | 9 | 9.5 | 6 | 15.5 | 24.5 | 28 | 30 | 14.5 | 2 |

Mean flow time = 12.87 hrs

Weighted mean flow time = 16.23 hrs

Mean lateness = 7.875 hrs

No. of tardy jobs = 0

Maximum lateness = 12.5 hrs

## 5.4 Critical ratio approach

The critical ratio is calculated by the ratio of time remaining before the due date and remaining processing time. The smallest CR goes first. For conditional mean tardiness which is a ratio of mean tardiness and proportion of jobs tardy, critical ratio priorities are effective. These approaches are used in computer software [114]. The calculations regarding the sequence of operations using the 'CR' rule are represented in Table 5.4.

Table 5.4 Scheduling using 'CR' rule

| $S$ | $P_j$ | $T_{sp}$ | $T_s$ | $CR$ |
|---|---|---|---|---|
| K38 | 3.5 | 7 | 3.5 | 2 |
| 206 G | 2 | 9 | 7 | 4.5 |
| KTE | 4 | 20 | 16 | 5 |
| KWPG | 6 | 28 | 22 | 4.67 |

At time 2 min part K38 completed, CR values are given in Table 5.4. At time 4min part 206 G completed, CR values are given in Table 5.5.

Table 5.5 Cr values after part K38 completed

| $S$ | $P_j$ | $T_{sp}$ | $CR$ |
|---|---|---|---|
| 206 G | 2 | 9 | 7/2=3.5 |
| KTE | 4 | 20 | 18/4=4.5 |
| KWPG | 6 | 28 | 26/6=4.33 |

Table 5.6 Cr values after part K38 and 206 G completed

| $S$ | $P_j$ | $T_{sp}$ | $T_s$ |
|---|---|---|---|
| KTE | 4 | 20 | 16/4=4 |
| KWPG | 6 | 28 | 24/6=4 |

Since they both have the same critical ratio, and we compare processing time then KTE has less processing time. So, at time 8 min, KTE completed, and at time 14 min KWPG will be completed.

So, scheduling order will be K38 → 206G → KTE → KWPG.

Table 5.7 Sequence of operations using critical ratio approach

| $S$ | $T_j$ | $T_b$ | $P_j$ | $T_{fi}$ | $T_{fl}$ | $T_{sp}$ | $T_{ap}$ | $T_{he}$ | $T_{hpd}$ |
|---|---|---|---|---|---|---|---|---|---|
| K38 | 2 | 0 | 3.5 | 3.5 | 5.5 | 7 | 10 | 6.5 | 3 |
| 206 G | 1 | 3.5 | 2 | 5.5 | 6.5 | 9 | 12 | 6.5 | 3 |
| KTE | 7 | 5.5 | 4 | 9.5 | 16.5 | 28 | 30 | 20.5 | 2 |
| KWPG | 9 | 11.5 | 6 | 17.5 | 23.5 | 20 | 23 | 5.5 | 3 |

Mean flow time = 13 hrs

Weighted mean flow time = 16.17 hrs

Mean lateness = 7 hrs

No. of tardy jobs = 0

Maximum lateness = 10.5 hrs

## 5.5 LPT Approach

LPT approach is developed by Graham in 1969. Croce F Della et al. solved the identical parallel machine scheduling problem using the LPT rule. In the LPT rule, jobs are sequenced in descending order of processing times [74]. The calculations regarding the sequence of operations using the LPT approach are represented in Table 5.8.

Table 5.8 Sequence of operations using LPT approach

| $S$ | $T_j$ | $T_b$ | $P_j$ | $T_{fi}$ | $T_{fl}$ | $T_{sp}$ | $T_{ap}$ | $T_{he}$ | $T_{hpd}$ |
|---|---|---|---|---|---|---|---|---|---|
| KWPG | 9 | 0 | 6 | 6 | 15 | 28 | 30 | 24 | 2 |
| KTE | 7 | 6 | 4 | 10 | 17 | 20 | 25 | 15 | 5 |
| K 38 | 2 | 10 | 3.5 | 13.5 | 15.5 | 7 | 12 | -1.5 | 5 |
| 206 G | 1 | 13.5 | 2 | 15.5 | 16.5 | 9 | 10 | -5.5 | 1 |

Mean flow time = 16 hrs

Weighted mean flow time = 15.92 hrs

Mean lateness = 4.75 hrs

Mean tardiness =3.25 hrs

No. of tardy jobs = 2

Maximum tardiness = 6.5 hrs (job 206G & K38)

Maximum lateness = 22 hrs

### 5.6 WSPT Approach

In the WSPT approach, the processing time to weight ratio is calculated and jobs are arranged according to the increasing order of these ratios. In this study, weights are assigned according to scheduled customer pickup time. Table 5.9 shows the calculation of these ratios. The calculations regarding the sequence of operations using the WSPT approach are represented in Table 5.10.

Table 5.9 Process time to weights ratio calculation

| $Partname$ | $P_j$ | $W_j$ | $P_j/W_j$ |
|---|---|---|---|
| K38 | 3.5 | 0.13 | 26.92 |
| 206 G | 2 | 0.17 | 11.76 |
| KTE | 4 | 0.3 | 13.33 |
| KWPG | 6 | 0.4 | 15 |

The part sequence obtained using the WSPT approach- ($206G \rightarrow$ KTE $\rightarrow$ KWPG $\rightarrow$ K38)

Table 5.10 Sequence of operations using the WSPT approach

| $S$ | $T_j$ | $T_b$ | $P_j$ | $T_{fi}$ | $T_{fl}$ | $T_{sp}$ | $T_{ap}$ | $T_{he}$ | $T_{hpd}$ |
|---|---|---|---|---|---|---|---|---|---|
| 206 G | 1 | 0 | 2 | 2 | 3 | 9 | 10 | 8 | 1 |
| KTE | 7 | 2 | 4 | 6 | 13 | 20 | 25 | 19 | 5 |
| KWPG | 9 | 6 | 6 | 12 | 21 | 28 | 30 | 18 | 2 |
| K38 | 2 | 12 | 3.5 | 15.5 | 17.5 | 7 | 12 | -3.5 | 5 |

Mean flow time = 13.625 hrs

Weighted mean flow time = 15.08 hrs

Mean lateness = -7.125 hrs

Mean tardiness = 2.125 hrs

No. of tardy jobs = 1

Maximum tardiness = 8.5 hrs (job K38)

Maximum lateness = 16 hrs (job KWPG)

### 5.7 COVERT Approach

In the COVERT approach, the tardiness to processing time ratio is calculated and based on the largest ratio first, a part sequence is selected. This rule is very effective in minimizing average conditional tardiness. The lateness of job j is defined by Eq. (45). Positive lateness is known as tardiness. The calculations regarding the sequence of operations using the COVERT approach are represented in Table 5.12.

$$L_j = T_{fi} - T_d \tag{45}$$

Table 5.11 Calculation of COVERT ratio

| Part lot | $T_j$ | $P_j$ | $T_d$ | $T_{fi}$ | $L_j$ | COVERT Ratio |
|---|---|---|---|---|---|---|
| K38 | 2 | 3.5 | 7 | 3.5 | -3.5 | -1 |
| 206 G | 1 | 2 | 9 | 5.5 | -3.5 | -1.75 |
| KTE | 7 | 4 | 20 | 9.5 | -10.5 | -2.62 |
| KWPG | 9 | 6 | 28 | 15.5 | -12.5 | -2.08 |

Based on this ratio, the part sequence selected is (K38 → 206G → KWPG → KTE)

Table 5.12 Sequence of operations using COVERT approach

| $S$ | $T_j$ | $T_b$ | $P_j$ | $T_{fi}$ | $T_{fl}$ | $T_{sp}$ | $T_{ap}$ | $T_{he}$ | $T_{hpd}$ |
|---|---|---|---|---|---|---|---|---|---|
| K38 | 2 | 0 | 3.5 | 3.5 | 5.5 | 7 | 12 | 8.5 | 5 |
| 206G | 1 | 3.5 | 2 | 5.5 | 6.5 | 9 | 10 | 4.5 | 1 |
| KWPG | 9 | 5.5 | 6 | 11.5 | 20.5 | 28 | 30 | 18.5 | 2 |
| KTE | 7 | 11.5 | 4 | 15.5 | 22.5 | 20 | 25 | 9.5 | 5 |

Mean flow time = 13.75 hrs

Weighted mean flow time = 16.77 hrs

Mean lateness = 7 hrs

Maximum lateness = 16.5 (Job KWPG)

No. of tardy jobs = 0

## 5.8 HODGSON'S Algorithm

This algorithm provides the best result in minimizing no. of tardy jobs and it is applicable for only those cases in which no. of tardy jobs are more than one. This algorithm sequences the job with the EDD sequence. In our study, we get no. of tardy jobs is zero according to the EDD sequence which shows optimal sequence [164].

# Chapter-6

# Case Study-3

## Energy efficient fuzzy scheduling system for crankcase covers manufacturing

Scheduling of automotive part manufacturing is more arduous and complex task. It is a very backbreaker task to get an optimum schedule for any automotive part manufacturing. In today's scenario, every industry and research organization need an energy-efficient system to cope up with the global environment. In this study, a first-time energy-efficient fuzzy scheduling system is developed for crankcase cover manufacturing under uncertain processing times. This study consists of the development of an energy-efficient fuzzy inference system of the four-crankcase cover (cover left side crankcase KWPG, cover left crankcase K38, cover crankcase 206 G, and cover right crankcase KTE) and its results are validated by the fuzzy set approach. This study consists of three inputs each for job prioritization and route selection of the crankcase cover. Inputs are further divided into three ranges for developing 27 rules in the fuzzy logic system. Fuzzy logic provides a decision by a combination of the rules for selecting job priorities and route selection. This scheduling system also provides the trade-off between energy consumption and makespan. Job priority sequence obtained by both fuzzy techniques for four crankcase cover problems is K38 > KWPG > 206G > KTE. This study is very useful for all automotive industries as well as research organizations.

### 6.1 Development of Mamdani fuzzy scheduling system

Mamdani fuzzy scheduling system is used to estimate job prioritization and route selection. The set of output data is obtained through the given input condition in the system. The proposed Mamdani fuzzy scheduling system for job prioritization and route selection is presented in Fig. 6.1 and Fig. 6.2.

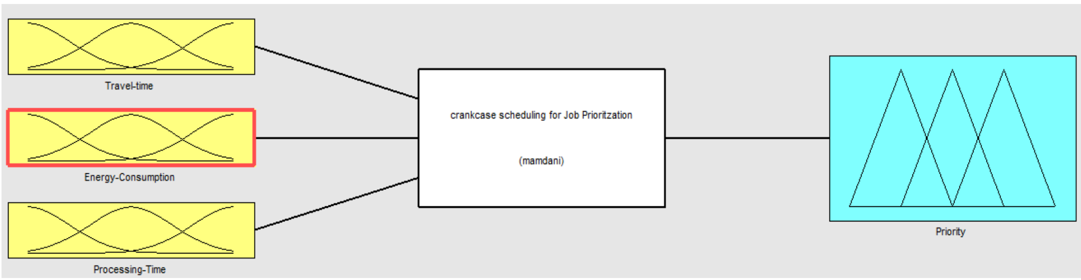


Fig. 6.1 Structure of Mamdani fuzzy rule-based system for evaluating job prioritization

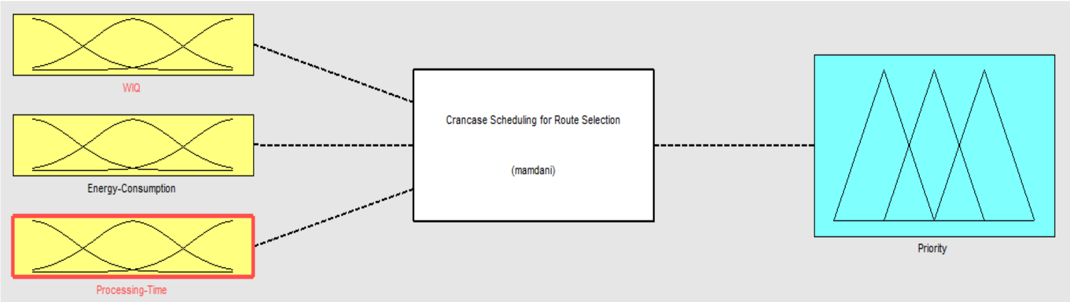


Fig. 6.2 Structure of Mamdani fuzzy rule-based system for route selection

The input variables for job prioritization are identified as processing time, travel time, energy consumption, and the output variable is the priority. The input variables for route selection are identified as work in queue, processing time, energy consumption and the output variable is the priority. The triangular membership function is used for defining the output and input variables.

In the fuzzy logic system, the inputs cycle time, due date, and energy consumption and have three membership functions each and each input is further divided into three states low, medium, and high. Thus, a total of 27 rules can be made for job prioritization. Similarly, the inputs work in queue, cycle time, and energy consumption for route selection have three membership functions and they are also divided into three states low, medium, and high. Thus, a total of 27 rules can also be made for route selection.

Defuzzification is the process of linguistic values into crisp values. There are commonly three techniques used for defuzzification as described below [249].

(a) Center of Gravity method
(b) Mean of Maximum method
(c) Height method

### *6.1.1 Problem definition*

Our main problem is how to get an optimum schedule for crankcase cover manufacturing. For obtaining the optimum schedule, we have used the fuzzy inference system and the fuzzy set approach. This study consists of the scheduling of four crankcase cover namely cover left side crankcase KWPG, cover left crankcase K38, cover crankcase 206 G, and cover right crankcase KTE as shown in Fig. 5.1 to Fig. 5.4.

*6.1.2 Assumptions made in the present work*

The following assumptions were made:

1. Setup times are assumed to be constant.
2. It is assumed that all the tools are available when needed.
3. Dynamic uncertainty is not taken into consideration i.e., the machines are not subject to any failure.
4. Each workstation can process only one job at a time.
5. There can be multiple routes possible for the jobs for sending them to different workstations and each route may have a different cycle time.
6. Delays in accessing any set of information are assumed to be negligible.
7. The Speed of all the laborers is supposed to be constant i.e., it is independent of the weight and size of jobs.
8. Orders arrive in the system randomly. So, crankcase cover manufacturing processes are assumed Poisson distributed.

The input variables used in the fuzzy logic system in MATLAB to identify the job priority are:

(a) Processing time (20 to 40 minutes)

(b) Travel time (2 to 10 minutes)

(c) Energy Consumption (3 to 6 KW)

### 6.2 Crankcase covers prioritization the using fuzzy logic system

All the inputs and their corresponding ranges are entered in the FLS of MATLAB. These inputs are entered in the FIS editor as shown in Fig. 6.3. In the FIS editor, we can choose the defuzzification method. For this scheduling problem, the centroid defuzzification method is selected in the FIS editor.

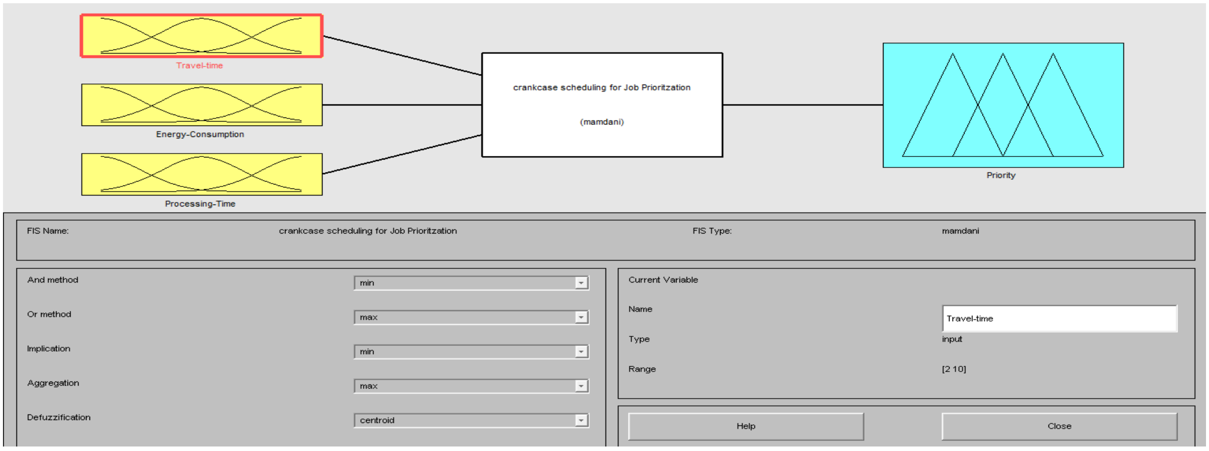


Fig. 6.3 FIS editor of job prioritization

All input variables for job priority are divided into three parts: small, medium, and high. The membership function editor for the job priorities is shown in Fig. 6.4.

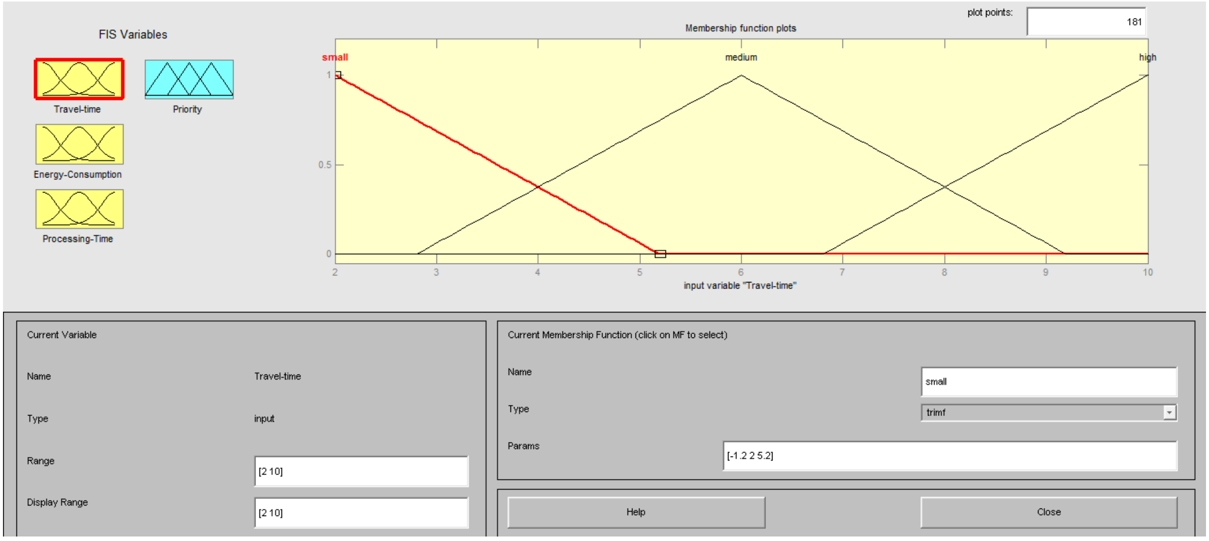


Fig. 6.4 Membership function editor for the job priorities

*6.2.1 Fuzzy rules for job prioritization*

Travel time, energy consumption, and processing time are the three main inputs/factors responsible for job prioritization. The output variable ‘priority’ is divided into nine categories which are minimum (MIN), negative low (NLO), low (LO), negative average (NAV), average (AV), positive average (PAV), high (HI), positive high (PHI), and maximum (MAX) shown in Fig. 6.6 [55]. The fuzzy rules for Job prioritization using these three inputs and one output (priority values) are given in Table 6.1. These rules are generated with the help of the literature review and expert views. The rule editor generated corresponding to these rules for Job prioritization is shown in Fig. 6.5.

Table 6.1 Fuzzy rule table for job prioritization

| Travel time | Energy consumption | | | Processing time |
|---|---|---|---|---|
| | High | Medium | Small | |
| Small | HI | PHI | MAX | Small |
| Medium | PAV | HI | PHI | Medium |
| High | MIN | NLO | NAV | High |
| Small | PAV | HI | PHI | Small |
| Medium | AV | PAV | HI | Medium |
| High | NLO | LO | NAV | High |
| Small | AV | PAV | HI | Small |
| Medium | NAV | AV | PAV | Medium |
| High | LO | NAV | AV | High |

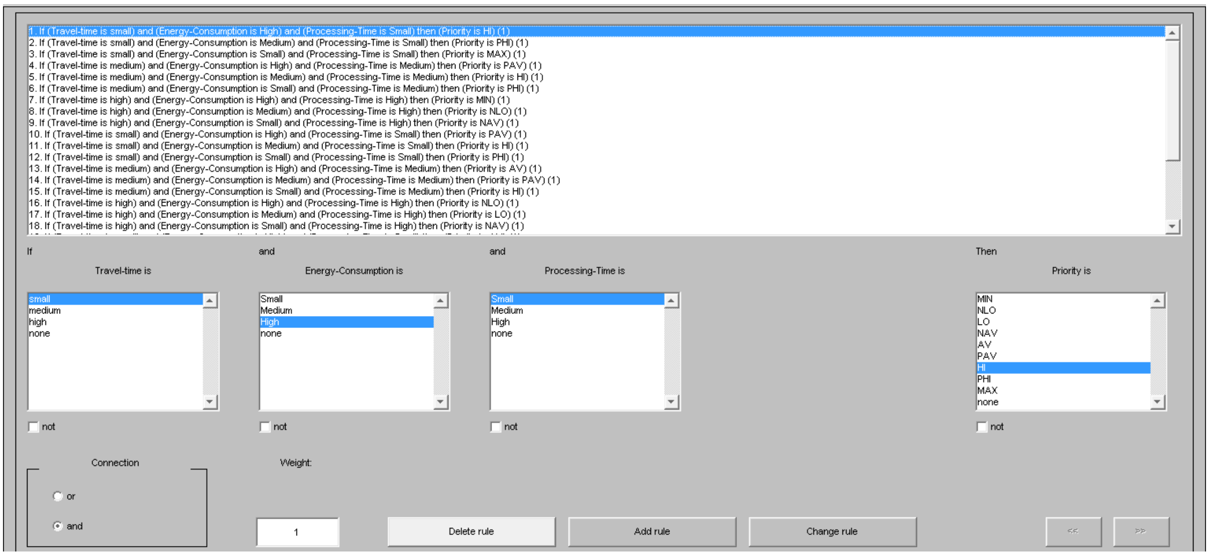


Fig. 6.5 Rule editor window

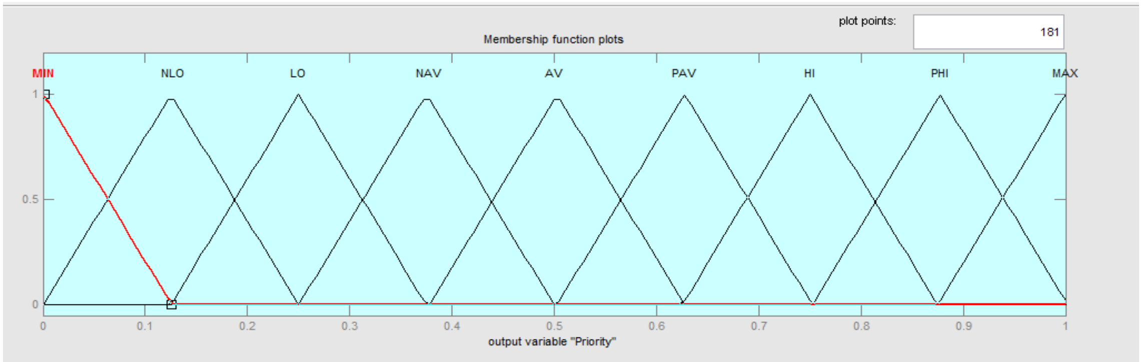


Fig.6.6 Membership function of the output variable ‘Priority’

## 6.3 Route selection calculation using fuzzy logic

Route selection can be done in two ways in the fuzzy logic system. These two ways are as follows:

1. Calculation and analysis using FLS in MATLAB
2. Calculation using the fuzzy set approach

### *6.3.1 Using FLS in MATLAB*

The fuzzy set approach is a manual calculation approach. We can do routing by making an FLS in MATLAB which takes less time than the fuzzy set approach. MATLAB approach is difficult to understand in comparison to the fuzzy set approach. MATLAB approach is simple if an equal contribution of inputs is taken. But it becomes a complex approach if we vary the contribution of inputs.

### *6.3.2 Fuzzy rules for route selection*

Among three variables for job prioritization, two variables are the same for route selection (energy consumption and processing time) and the third variable is taken is work in queue.

Their fuzzy rule for route selection of jobs using three inputs and one output is given in Table 6.2.

Table 6.2 Fuzzy rules for route selection of jobs

| Work in queue | Energy consumption | | | Processing time |
|---|---|---|---|---|
| | High | Medium | Small | |
| Small | NAV | NAV | NHI | Small |
| Medium | NLO | NAV | AV | Medium |
| High | MIN | NLO | NAV | High |
| Small | AV | HI | PHI | Small |
| Medium | LO | NAV | NAV | Medium |
| High | NLO | NAV | PAV | High |
| Small | HI | PHI | MAX | Small |
| Medium | PAV | HI | PHI | Medium |
| High | AV | PAV | HI | High |

*6.3.3 Route time calculation for all Jobs*

We have taken four crankcase covers on six machine scheduling problems. Some data has been collected from industry and some from the literature review. The processing times of various crankcase cover on different machines are shown in Table 6.3.

Table 6.3 Processing time (mins) of various crankcase cover

| M/c | KWPG | K38 | 206G | KTE |
|---|---|---|---|---|
| Cold chambers die casting machine (DCM) | 1.5 | 1.3 | 1.5 | 1.7 |
| Manual fettling (MF)/CNC fettling (CF) | 0.18/0.54 | 0.17/0.51 | 0.18/0.54 | 0.20/0.60 |
| Drilling machine (DM) | 0.25 | 0.15 | 0.40 | 0.50 |
| Vertical milling centre (VMC) | 3.5 | 2 | 4 | 6 |
| Polishing machine/Buffing machine (BM) | 0.22 | 0.21 | 0.22 | 0.23 |
| Surface treatment/Painting Shop (PS) | 20 | 19.15 | 22.7 | 23.4 |

Fettling is the most ignored process in the casting process. Fettling can be done manually (files, chisel, or hammer) or with some automatic CNC machine. Large casting like cylinder head or cylinder block requires a CNC machine for fettling whereas small and medium casting like crankcase cover for two-wheeler vehicles can be fettled manually. Route time of all four-crankcase cover on six machines is given in Table 6.4.

*6.3.4 Fuzzy set approach*

Each goal plays a significant role in finding the optimized route. Its contribution in terms of the membership function is shown in Table 6.5. The maximum value of $u_j(i)$ corresponds to the maximum value of $u_a(i)$ shown in Table 6.6.

Table 6.4 Route times for various crankcase cover

| Route (M/C sequence) | Work in queue | Processing time (mins) | Travel time (mins) | Energy consumption (KW) |
|---|---|---|---|---|
| Route times of crankcase cover KWPG | | | | |
| DCM-MF-DM-VMC-BM-PS | 10 | 25.65 | 6.4 | 5.1 |
| DCM-CF-DM-VMC-BM-PS | 8 | 26.01 | 6.5 | 5.6 |
| DCM-VMC-DM-VMC-BM-PS | 5 | 28.97 | 7.2 | 5.3 |
| Route times of crankcase cover K38 | | | | |
| DCM-MF-DM-VMC-BM-PS | 9 | 23 | 5.7 | 4.6 |
| DCM-CF-DM-VMC-BM-PS | 7 | 23.34 | 5.8 | 5.2 |
| DCM-VMC-DM-VMC-BM-PS | 4 | 24.83 | 6.2 | 4.9 |
| Route times of crankcase cover 206G | | | | |
| DCM-MF-DM-VMC-BM-PS | 13 | 29 | 7.2 | 5.3 |
| DCM-CF-DM-VMC-BM-PS | 11 | 29.36 | 7.3 | 5.7 |
| DCM-VMC-DM-VMC-BM-PS | 8 | 32.82 | 8.2 | 5.5 |
| Route times of crankcase cover KTE | | | | |
| DCM-MF-DM-VMC-BM-PS | 15 | 32.03 | 8 | 5.6 |
| DCM-CF-DM-VMC-BM-PS | 13 | 32.43 | 8.1 | 5.9 |
| DCM-VMC-DM-VMC-BM-PS | 11 | 37.83 | 9.4 | 5.8 |

Table 6.5 Membership function values

| Results corresponding to goal 1 | | | | Results corresponding to goal 2 | | | |
|---|---|---|---|---|---|---|---|
| $[u_1(1)]_{KWPG}$ | 0.717 | $[u_1(1)]_{K38}$ | 0.850 | $[u_2(1)]_{KWPG}$ | 0.625 | $[u_2(1)]_{K38}$ | 0.562 |
| $[u_1(2)]_{KWPG}$ | 0.699 | $[u_1(2)]_{K38}$ | 0.833 | $[u_2(2)]_{KWPG}$ | 0.500 | $[u_2(2)]_{K38}$ | 0.437 |
| $[u_1(3)]_{KWPG}$ | 0.551 | $[u_1(3)]_{K38}$ | 0.758 | $[u_2(3)]_{KWPG}$ | 0.312 | $[u_2(3)]_{K38}$ | 0.250 |
| $[u_1(1)]_{206G}$ | 0.550 | $[u_1(1)]_{KTE}$ | 0.398 | $[u_2(1)]_{206G}$ | 0.812 | $[u_2(1)]_{KTE}$ | 0.937 |
| $[u_1(2)]_{206G}$ | 0.532 | $[u_1(2)]_{KTE}$ | 0.378 | $[u_2(2)]_{206G}$ | 0.687 | $[u_2(2)]_{KTE}$ | 0.812 |
| $[u_1(3)]_{206G}$ | 0.359 | $[u_1(3)]_{KTE}$ | 0.108 | $[u_2(3)]_{206G}$ | 0.500 | $[u_2(3)]_{KTE}$ | 0.687 |

| Results corresponding to goal 3 | | | | Results corresponding to goal 4 | | | |
|---|---|---|---|---|---|---|---|
| $[u_3(1)]_{KWPG}$ | 0.550 | $[u_3(1)]_{K38}$ | 0.462 | $[u_4(1)]_{KWPG}$ | 0.700 | $[u_4(1)]_{K38}$ | 0.533 |
| $[u_3(2)]_{KWPG}$ | 0.562 | $[u_3(2)]_{K38}$ | 0.475 | $[u_4(2)]_{KWPG}$ | 0.867 | $[u_4(2)]_{K38}$ | 0.733 |
| $[u_3(3)]_{KWPG}$ | 0.650 | $[u_3(3)]_{K38}$ | 0.525 | $[u_4(3)]_{KWPG}$ | 0.767 | $[u_4(3)]_{K38}$ | 0.633 |
| $[u_3(1)]_{206G}$ | 0.650 | $[u_3(1)]_{KTE}$ | 0.750 | $[u_4(1)]_{206G}$ | 0.767 | $[u_4(1)]_{KTE}$ | 0.867 |
| $[u_3(2)]_{206G}$ | 0.662 | $[u_3(2)]_{KTE}$ | 0.762 | $[u_4(2)]_{206G}$ | 0.900 | $[u_4(2)]_{KTE}$ | 0.967 |
| $[u_3(3)]_{206G}$ | 0.775 | $[u_3(3)]_{KTE}$ | 0.925 | $[u_4(3)]_{206G}$ | 0.833 | $[u_4(3)]_{KTE}$ | 0.933 |

Table 6.6 Maximum value of $u_a(i)$ for different crankcase cover

| Route (M/C sequence) | KWPG | K38 | 206G | KTE |
|---|---|---|---|---|
| DCM-MF-DM-VMC-BM-PS | 0.648 | 0.602 | 0.695 | 0.738 |
| DCM-CF-DM-VMC-BM-PS | 0.657 | 0.619 | 0.695 | 0.729 |
| DCM-VMC-DM-VMC-BM-PS | 0.57 | 0.541 | 0.617 | 0.663 |

# Chapter-7

# Case Study-4

### Modelling and simulation of crankcase cover manufacturing in the automobile industry

The simulation creates the virtual production model which is exactly like the real environment, and it provides future insights before laying down the actual production plant layout. With the help of simulation, we can simulate the complex and costly manufacturing system without being investing money physically and check the system's real-life behavior. In this study, the first time the modelling and simulation of two-wheeler crankcase cover manufacturing are done with the help of flexsim. This study deals with the development of a simulation model for crankcase cover manufacturing systems in the automobile industry. Flexsim simulation tool is used as an optimization tool for analyzing the bottleneck or performing line balancing.

Table 7.1 represents the study of simulation-based papers consisting of the author's name, problem type, parameter optimized, and types of simulation. Bjorklund S. et al. solved the real-time forecasting problem with the help of flexsim simulation software [33]. Badri M. A. et al. utilized the simulation modelling concept for effective operations in hospital emergency cells by minimizing the waiting time, cost and increase the throughput, resource utilization, and efficiency of the system [25]. Cheng H. C. et al. developed a simulation model for machined component manufacturing in a flexible manufacturing system. They optimized the routing sequence of operations [60].

Peng Y. et al. applied the flexsim simulation method for improving productivity and reducing the cycle time in the assembly line problem [219]. Gong L. et al. developed a simulation model for automobile mixed assembly lines. They increased the machine utilization rate and efficiency and reduced the blockage rate in the assembly line [111]. Chandika S. et al. designed and simulated the micropump in the automobile industry using the INTELLISUITE software and optimized the fabrication cost [50]. Kesen S. E. et al. utilized the SIMAN simulation software for the analysis of the pull system to optimize the work-in-process inventory [149]. Lin C. K. Y. et al. developed a simulation-based heuristic algorithm for appointment scheduling and resource allocation [172]. Azab A. et al. utilized the simulation approach for minimizing waiting-time and emissions of trucks and enhanced the productivity of container terminals [23].

Table 7.1 Study of simulation-based papers

| Authors | Problem Type | Factors/Parameters | Type of Simulation |
|---|---|---|---|
| Bjorklund S. et al. [33] | Real-time forecasting problem | Machine failure times | Flexsim |
| Krishna L. S. R. et al. [160] | FMS Scheduling problem | Makespan | Flexsim |
| Fauadi M. et al. [96] | Warehouse logistic system problem | Space utilization, use of equipment & tools, work safety | Flexsim, Arena, and Promodel |
| Jarernram J. et al. [137] | Parallel machine scheduling problem | Makespan | Flexsim |
| Rodrigues R. P. et al. [232] | Jobshop Scheduling | Makespan and machine utilization | Agent-based simulation |
| Nie X. et al. [210] | Gantry crane scheduling problem | Operator efficiency and waiting time | Flexsim |
| Badri et al. [25] | Health services scheduling problem | Waiting time, cost, throughput, resource utilization, and efficiency | SLAMSYSTEM |
| Cheng H. C. et al.[61] | FMS Scheduling problem | Routing sequence of operations | Flexsim, OptQuest |
| Peng Y. et al. [219] | Assembly line problem | Productivity and reducing the cycle time | Flexsim |
| Gong L. et al. [111] | Assembly line problem | Machine utilization rate, efficiency, and blockage rate | Flexsim |
| Chandika S. et al. [50] | Micropump design problem | Fabrication cost | INTELLISUITE |
| Kesen S. E. et al. [149] | Pull system problem | Work-in-process inventory | SIMAN |
| Lin C. K. Y. et al. [172] | Appointment scheduling and resource allocation | Resource overtime, patient waiting time, and waiting area congestion | Simulation-based heuristic algorithm |
| Azab A. et al. [23] | Trucks appointment scheduling problem | Waiting time and productivity of container terminals | Flexsim |
| Nathan Huynh [126] | Trucks appointment scheduling problem | Truck turn time and resource utilization | Flexsim |
| Kim S. et al. [154] | Machine shop scheduling problem | Productivity and energy cost | Anylogic |
| Phani K. et al. [222] | Job shop scheduling problems | Total processing time, machine utilization, and allocation of jobs | Flexsim |
| Steinhauer D. et al. [244] | Production planning Problem | Uncertainty and robustness of Production planning | GeneSim |
| Wang Y. R. et al. [277] | Logistics system problem | Production efficiency | Flexsim and Petri net |

Krishna L. S. R. et al. used the flexsim simulation-based approach for analyzing the effect of buffers on a flexible manufacturing system (FMS) performance [160]. Nathan Huynh analyzed the effects of varying scheduling rules on the truck turn time and resource utilization [126]. Kim S. et al. developed the simulation-based scheduling system for machine shop operations of the manufacturing industry of the USA to optimize the productivity and energy cost [154]. Jarernram J. et al. solved the parallel machine scheduling problem using flexsim simulation software and optimized the makespan [137]. Rodrigues R. P. et al. developed the hybrid simulation model and solved the multi-objective problems to optimize the makespan and machine utilization [232].

Nie X. et al. optimized the operator efficiency and waiting time of the gantry crane using the simulation approach of flexsim and find out the best operating scheduling mode of gantry crane [210]. Phani K. et al. optimized the total processing time, machine utilization, and allocation of jobs in job shop scheduling problems using the simulation approach based on the flexsim [222]. Steinhauer D. et al. presented a simulation approach for reducing the uncertainty for optimizing the quality and robustness of production planning in shipbuilding [244]. Wang Y. R. et al. utilized the flexsim and Petri net simulation model for optimizing the production efficiency of the logistics system of the automobile industry [277]. The past studies show that most of the researchers have successfully utilized the flexsim tool for modelling and simulation problems. It is also found from the literature review that the modelling and simulation of crankcase cover manufacturing in the automobile industry is an untouched area of research. This study initially aims to develop the 3D simulation model based on the generic process model. Later, the bottleneck will be identified, and removed for increasing production line efficiency and production throughput.

## 7.1 Process model

For simulating the layout of any industry, the first step is to analyze the process model. The next step is to convert this process model into a simulation model. Flexsim is a powerful tool for converting any chimerical process model into a realistic 3d simulation model. The crankcase cover manufacturing process consists of the processes such as the melting of raw material in the furnace, die casting process, fettling process, drilling process, machining process, buffing process, surface treatment, or painting process. The general process model for the crankcase cover manufacturing process is shown in Fig. 1.9. Our main aim of the study is to find out the bottleneck present in the production line and to eliminate this bottleneck to increase the line efficiency.

## 7.2 Flexsim simulation approach

Flexsim simulation software tool is used for developing a simulation model of the crankcase cover manufacturing process. This tool provides a 3-D model that can be analyzed without establishing it in the physical form [150].

### *7.2.1 Assumptions*

The following assumptions are considered while developing a simulation model.

(i) All machines have enough capacity to operate.

(ii) The arrival rate of raw materials is assumed to be an exponential distribution with a location value of zero and a scale value of 4 minutes.

(iii) The setup time is assumed to be a triangular distribution with min time 0.05 minutes, max time 0.15 minutes but most commonly time 0.01 minutes.

(iv) The processing time is also assumed to be triangular distribution.

Flexsim contains the four basic objects as shown in Fig. 7.1. These objects are a source, sink, processor, and queues [150].

### *7.2.2 Simulation model*

There are generally 3 inputs of the simulation model which are arrival rate, processing time, and the number of resources. The model output is generally measured in terms of throughput, utilization, and states. The flow items of this simulation model are crankcase covers. The fixed resources used in this simulation model are the source, queue, processor, and sink. Updating the virtual model is necessary using the company's real database system from time to time. Fig. 7.2 represents the 3D simulation model of crankcase cover manufacturing. For running this simulation model there is a need of defining the model parameters. These model parameters are defined in Table 7.2 with their statistical distributions and values.

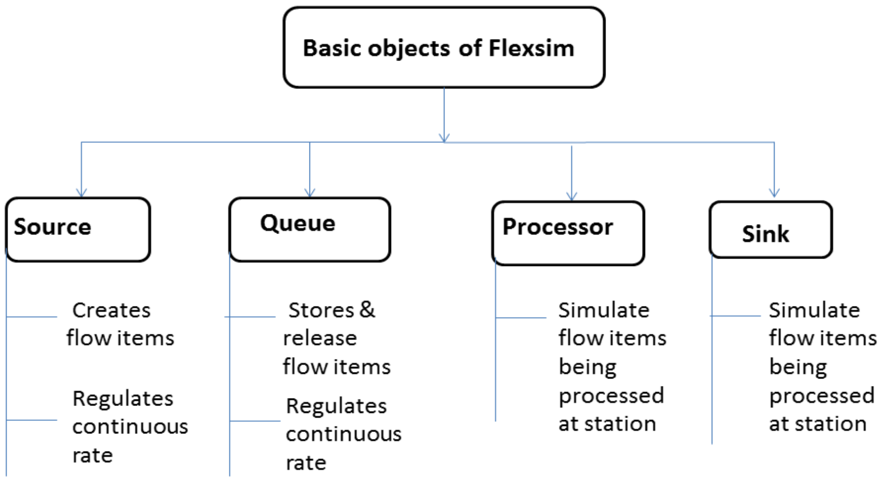


Fig. 7.1 Basics objects of Flexsim

During the simulation, the reset and the run option are used in flexsim for running the model, and the dashboard option provides all analysis of the manufacturing system in terms of various charts. Analysis of the virtual model eliminates any uncertainty present in the production system.

Table 7.2 Simulation model parameters

| Model parameters | Distribution | Values (mins) |
|---|---|---|
| Arrival rate of raw materials | Exponential | 2.00 |
| Setup time | Triangular | 0.01 |
| Die casting machine (DCM) | Triangular | 1.50 |
| Manual fettling (MF) | Triangular | 0.18 |
| Drilling machine (DM) | Triangular | 0.35 |
| Vertical milling center (VMC) | Triangular | 4.00 |
| Buffing machine (BM) | Triangular | 0.22 |

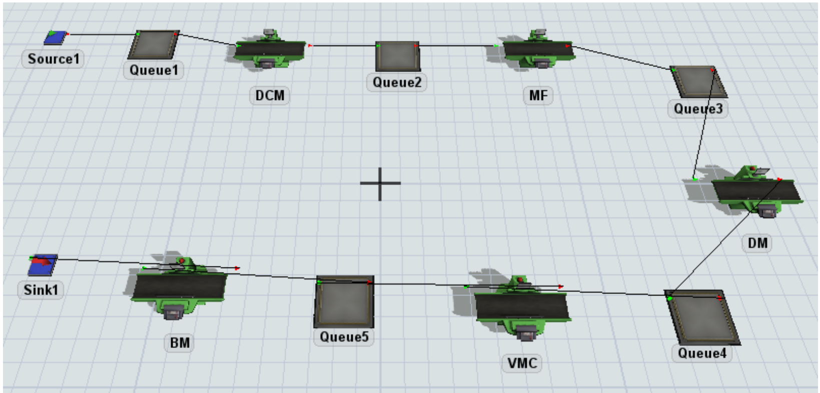


Fig. 7.2 Simulation model of crankcase cover manufacturing

### 7.3 Elimination of bottleneck in production line

The run speed during simulation is taken as 2401 sec. On running the simulation model for 8-hour (28800 sec) shift, it has been observed that the bottleneck is created on the queue 4 as shown in Fig. 7.3. The production line efficiency of this model is calculated as 51.8%. Fig. 7.4 is showing the throughput during 8-hour shift. It can also be seen from this diagram that bottleneck is present after drilling machine due to which throughput value of VMC is 115 as compared to 218 value of drilling machine. Since the bottleneck is created before VMC machine, So, add one more VMC machine in production line as shown in Fig. 9.14. After removing this bottleneck, the production line efficiency becomes 97.29%. The increase in throughput value after eliminating bottleneck is also shown in Fig. 9.15.

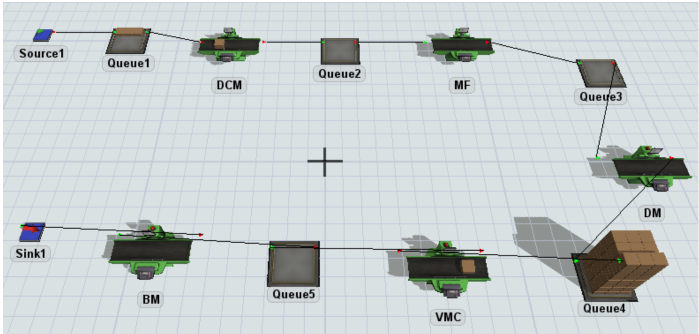


Fig. 7.3 Simulation model showing bottleneck on queue 4

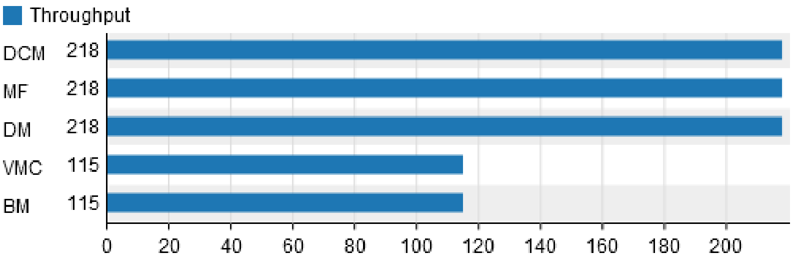


Fig. 7.4 Throughput during 8-hour shift

# Chapter-8

# Case Study 5

**Prioritizing scheduling parameters in automotive industry using fuzzy TOPSIS-DEMATEL model**

The Automotive industry is one of the biggest emerging sectors in terms of revenue. Every automotive industry has an indispensable need for optimum manufacturing scheduling systems for generating good revenues and profits. This need can be pulled off by identifying and prioritizing the scheduling parameters. MCDM is one of the best techniques of operation research in selecting the best parameters or factors among the various alternatives. This study includes the identification and prioritization of the various important scheduling parameters in the Indian automotive industry. The twelve scheduling parameters have been identified in this study and these parameters are prioritized by the fuzzy TOPSIS and DEMATEL. These methods best deal with uncertainty and vagueness. The first time, fuzzy TOPSIS and DEMATEL are applied in prioritizing the SPs in the automobile industry. The expert's views are gathered from the five automobile industries. Makespan, energy consumption, due date, and travel time are the crucial parameters obtained using Fuzzy TOPSIS. The least important parameters obtained using Fuzzy TOPSIS are work in process, flow time, and release date. The most influential parameters identified using the DEMATEL method are completion time and processing time. This study is valuable for every industry and research organization in the field of the automobile industry.

In today's scenario, the desideratum of every manufacturing firm is scheduling. Scheduling means fulfilling the different performance criteria or factors by distributing the available production resources over time [10]. Several operations have to be performed on the different sets of jobs for their completion in the scheduling problem. The different resources and machines are required for performing different job operations [122]. Production Scheduling is a very important decision-making process that includes the proper allocation of all the available resources for performing all tasks [7]. On-time delivery of products or services provides customer satisfaction and scheduling helps in achieving on-time delivery [223]. The primary objective of scheduling includes determining the job processing time, sequence, and due date of jobs [252]. The complexity of each production scheduling problem depends on different objectives, environmental conditions, and process constraints. The manufacturing schedule depends not only on production but also depends on scheduling parameters [73]. Prioritizing scheduling parameters is the need of every industry for optimum schedule because, without an optimum schedule, industries can't increase the profit and productivity on a full scale. Most of the industries only work in improving the work culture, surrounding conditions, and performance of workers and machines, etc. But for every industry, it is important to identify and prioritize the critical scheduling parameters or most influential scheduling parameters of their respective area or field. By identifying the Critical Scheduling parameters, we can generate the most effective scheduling system. So, there is an immense need of prioritizing these parameters. These parameters can be effectively prioritized using the MCDM approach. This study includes the identification of scheduling parameters and finding the criticality of these parameters in the automobile industry.

Due to uncertainty and ambiguity in human judgment decisions, all values corresponding to scheduling parameters in the decision set can't be crisp. So, some linguistic variable or fuzzy variable must be taken to deals with all the criteria [302]. Therefore, fuzzy TOPSIS methodology is used in this study for prioritizing the SPs for an optimum schedule in the automotive industry, and the DEMATEL method is used for identifying the most influential parameters and finds cause criteria and effect criteria group. DEMATEL is the structural modeling approach used in finding the relationship between the cause-and-effect criteria. Many researchers have used fuzzy TOPSIS and DEMATEL methodology separately in various scheduling problems as discussed in the literature part. But the first time, both these approaches are applied simultaneously in prioritizing the scheduling parameters and identify the most influential parameters for an optimum schedule in the automobile industry.

## 8.1 Identification of Scheduling parameters for optimum schedule generation

Twelve Scheduling parameters are identified from previous studies and industry expert's reviews. These parameters are discussed as follows. Makespan is one of the strongest performance measures in all types of scheduling problems and it represents the total time to process all the jobs [223]. For minimizing the makespan, machine speed can be increased but it increases energy consumption. The trade-off is required between these parameters [112]. Makespan or tardiness is taken as the main parameter for a single optimality criteria problem [231]. Flow time represents the size of the average inventory. Flow time can be significantly reduced by minimizing the average inventory. Lateness indicates the condition of completing the orders near the due date [280].

Processing time depends on the starting time in machine scheduling problems. Processing time can be linear or exponential in time-dependent problems [62]. The release date shows the value before which a job cannot be processed on a machine [11]. A job must be entered at the release date and leaves at the due date [224]. Earliness represents the negative lateness and shows the condition of completing the orders earlier to the due date [11].

### 8.2 Application of Fuzzy TOPSIS methodology

Literature review and experts view from various decision-making companies help us in identifying the main twelve scheduling parameters for the optimum schedule in automotive part manufacturing companies. The twelve scheduling parameters identified are makespan, flow time, lateness, processing time, due date, energy consumption, earliness, travel time, work in process, tardiness, completion time, and release date. Profiles of the various crankcase automotive part manufacturing companies are illustrated in Table 8.1.

Table 8.1 Profile of various decision-maker companies

| Companies | Product Manufactured | Material | Annual Turnover (USD) | No. of Branches in India | Manufacturing Facility Setup in India |
|---|---|---|---|---|---|
| Super Auto India limited (CPY 1) | Motorcycle crankcase | Aluminum | 70 Lakh | 3 | Faridabad, Pune |
| Shiv Shakti Engineering Co. (CPY 2) | Ingersoll Rand Crank Case | CIFC225 | 1.4 Lakh | 1 | Ahmedabad (Gujarat, India) |
| Kolben Compressor Spares (India) Private Limited (CPY 3) | Vilter 440 Crankcase | Steel | 35 Lakh | 1 | Churchgate, Mumbai, Maharashtra |
| Industrial Spare Syndicate Limited (CPY 4) | ISS Crank Case for KG2 | Cast Iron | 4.9 Lakh | 1 | Mori Gate, Delhi |
| Shanirajeshwar Die Casting Pvt. Ltd. (CPY 5) | Black Automobile Crankcase | Aluminum Alloy | 24.5 Lakh | 1 | Moshi, Pune, Maharashtra |

Table 8.3 is showing the linguistic variable based decision matrix. This matrix is developed on the five-point linguistic scale. This linguistic scale with its fuzzy number is specified in Table 3.1. The fuzzy number-based decision matrix table as obtained from step 1 is represented in Table 8.4.

Table 8.2 Scheduling parameters for optimum schedule

| Scheduling Parameters | Symbol |
|---|---|
| Makespan | $M_k$ |
| Flow time | $F_t$ |
| Lateness | $L_t$ |
| Processing time | $P_t$ |
| Due Date | $D_d$ |
| Energy consumption | $E_c$ |
| Earliness | E |
| Travel time | $T_t$ |
| Work in Process | $W_p$ |
| Tardiness | T |
| Completion time | $C_t$ |
| Release date | $R_d$ |

Table 8.3 Linguistic variable-based decision matrix

| | CPY 1 | CPY 2 | CPY 3 | CPY 4 | CPY 5 |
|---|---|---|---|---|---|
| $M_k$ | HI | HI | PHI | HI | PHI |
| $F_t$ | NLO | AM | LO | NLO | LO |
| $L_t$ | LO | AM | LO | LO | AM |
| $P_t$ | HI | HI | AM | HI | AM |
| $D_d$ | HI | PHI | AM | HI | AM |
| $E_c$ | HI | AM | AM | LO | AM |
| E | LO | AM | LO | LO | LO |
| $T_t$ | AM | HI | AM | HI | AM |
| $W_p$ | NLO | AM | NLO | NLO | LO |
| T | HI | AM | AM | HI | AM |
| $C_t$ | LO | AM | AM | LO | AM |
| $R_d$ | LO | AM | LO | NLO | LO |

Table 8.4 Fuzzy number-based decision matrix

| | CPY 1 | CPY 2 | CPY 3 | CPY 4 | CPY 5 |
|---|---|---|---|---|---|
| $M_k$ | 5,7,9 | 5,7,9 | 7,9,9 | 5,7,9 | 7,9,9 |
| $F_t$ | 1,1,3 | 3,5,7 | 1,3,5 | 1,1,3 | 1,3,5 |
| $L_t$ | 1,3,5 | 3,5,7 | 1,3,5 | 1,3,5 | 3,5,7 |
| $P_t$ | 5,7,9 | 5,7,9 | 3,5,7 | 5,7,9 | 3,5,7 |
| $D_d$ | 5,7,9 | 7,9,9 | 3,5,7 | 5,7,9 | 3,5,7 |
| $E_c$ | 5,7,9 | 3,5,7 | 3,5,7 | 1,3,5 | 3,5,7 |
| E | 1,3,5 | 3,5,7 | 1,3,5 | 1,3,5 | 1,3,5 |
| $T_t$ | 3,5,7 | 5,7,9 | 3,5,7 | 5,7,9 | 3,5,7 |
| $W_p$ | 1,1,3 | 3,5,7 | 1,1,3 | 1,1,3 | 1,3,5 |
| T | 5,7,9 | 3,5,7 | 3,5,7 | 5,7,9 | 3,5,7 |
| $C_t$ | 1,3,5 | 3,5,7 | 3,5,7 | 1,3,5 | 3,5,7 |
| $R_d$ | 1,3,5 | 3,5,7 | 1,3,5 | 1,1,3 | 1,3,5 |

For calculating the normalized fuzzy decision matrix, we have assumed all criteria to be non-beneficial (cost) criteria. The matrix $V$ will be the same as the matrix $R_{ij}$ because, for this study, equal weights are considered for all the decision-makers. Table 8.5 shows the matrix $V$ with the fuzzy ideal solutions. The distances or separation from the ideal solutions are calculated in Table 8.6 and Table 8.7.

Table 8.5 Matrix $V$ with ideal solutions

| | CPY 1 | CPY 2 | CPY 3 | CPY 4 | CPY 5 |
|---|---|---|---|---|---|
| $M_k$ | 0.11,0.14,0.2 | 0.33,0.42,0.6 | 0.11,0.11,0.14 | 0.11,0.14,0.2 | 0.11,0.11,0.14 |
| $F_t$ | 0.33,1,1 | 0.42,0.6,1 | 0.2,0.33,1 | 0.33,1,1 | 0.2,0.33,1 |
| $L_t$ | 0.2,0.33,1 | 0.42,0.6,1 | 0.2,0.33,1 | 0.2,0.33,1 | 0.14,0.2,0.33 |
| $P_t$ | 0.11,0.14,0.2 | 0.33,0.42,0.6 | 0.14,0.2,0.33 | 0.11,0.14,0.2 | 0.14,0.2,0.33 |
| $D_d$ | 0.11,0.14,0.2 | 0.33,0.33,0.42 | 0.14,0.2,0.33 | 0.11,0.14,0.2 | 0.14,0.2,0.33 |
| $E_c$ | 0.11,0.14,0.2 | 0.42,0.6,1 | 0.14,0.2,0.33 | 0.2,0.33,1 | 0.14,0.2,0.33 |
| E | 0.2,0.33,1 | 0.42,0.6,1 | 0.2,0.33,1 | 0.2,0.33,1 | 0.2,0.33,1 |
| $T_t$ | 0.14,0.2,0.33 | 0.33,0.42,0.6 | 0.14,0.2,0.33 | 0.11,0.14,0.2 | 0.14,0.2,0.33 |
| $W_p$ | 0.33,1,1 | 0.42,0.6,1 | 0.33,1,1 | 0.33,1,1 | 0.2,0.33,1 |
| T | 0.11,0.14,0.2 | 0.42,0.6,1 | 0.14,0.2,0.33 | 0.11,0.14,0.2 | 0.14,0.2,0.33 |
| $C_t$ | 0.2,0.33,1 | 0.42,0.6,1 | 0.14,0.2,0.33 | 0.2,0.33,1 | 0.14,0.2,0.33 |
| $R_d$ | 0.2,0.33,1 | 0.42,0.6,1 | 0.2,0.33,1 | 0.33,1,1 | 0.2,0.33,1 |
| **$A^+$** | 0.33,1,1 | 0.42,0.6,1 | 0.33,1,1 | 0.33,1,1 | 0.2,0.33,1 |
| **$A^-$** | 0.11,0.14,0.2 | 0.33,0.33,0.42 | 0.11,0.11,0.14 | 0.11,0.14,0.2 | 0.11,0.11,0.14 |

Table 8.6 Separation from each parameter to the FPIS

| | CPY 1 | CPY 2 | CPY 3 | CPY 4 | CPY 5 |
|---|---|---|---|---|---|
| $M_k$ | 0.689 | 0.258 | 0.725 | 0.689 | 0.515 |
| $F_t$ | 0 | 0 | 0.394 | 0 | 0 |
| $L_t$ | 0.394 | 0 | 0.394 | 0.394 | 0.395 |
| $P_t$ | 0.689 | 0.258 | 0.612 | 0.689 | 0.395 |
| $D_d$ | 0.689 | 0.373 | 0.612 | 0.689 | 0.395 |
| $E_c$ | 0.689 | 0 | 0.612 | 0.394 | 0.395 |
| E | 0.394 | 0 | 0.394 | 0.394 | 0 |
| $T_t$ | 0.612 | 0.258 | 0.612 | 0.689 | 0.395 |
| $W_p$ | 0 | 0 | 0 | 0 | 0 |
| T | 0.689 | 0 | 0.612 | 0.689 | 0.395 |
| $C_t$ | 0.394 | 0 | 0.612 | 0.394 | 0.395 |
| $R_d$ | 0.394 | 0 | 0.394 | 0 | 0 |

Table 8.7 Separation from each parameter to the FNIS

| | CPY 1 | CPY 2 | CPY 3 | CPY 4 | CPY 5 |
|---|---|---|---|---|---|
| $M_k$ | 0 | 0.116 | 0 | 0 | 0 |
| $F_t$ | 0.689 | 0.373 | 0.515 | 0.689 | 0.515 |
| $L_t$ | 0.477 | 0.373 | 0.515 | 0.477 | 0.122 |
| $P_t$ | 0 | 0.116 | 0.122 | 0 | 0.122 |
| $D_d$ | 0 | 0 | 0.122 | 0 | 0.122 |
| $E_c$ | 0 | 0.373 | 0.122 | 0.477 | 0.122 |
| E | 0.477 | 0.373 | 0.515 | 0.477 | 0.515 |
| $T_t$ | 0 | 0.116 | 0.122 | 0 | 0.122 |
| $W_p$ | 0.689 | 0.373 | 0.725 | 0.689 | 0.515 |
| T | 0 | 0.373 | 0.122 | 0 | 0.122 |
| $C_t$ | 0.477 | 0.373 | 0.122 | 0.477 | 0.122 |
| $R_d$ | 0.477 | 0.373 | 0.515 | 0.689 | 0.515 |

## 8.3 Application of DEMATEL methodology

The influence of each criterion on all other criteria is represented by the initial direct relation matrix in terms of numerical value as shown in Table 8.8. Data for Table 8.8 is collected from the literature review and industry experts. A total relation matrix is generated by using their equations as shown in Table 8.9. The positive and negative values of D-R represent the cause-and-effect criteria respectively as depicted in Table 8.10.

Table 8.8 Initial direct relation matrix (M)

| | $M_k$ | $F_t$ | $L_t$ | $P_t$ | $D_d$ | $E_c$ | E | $T_t$ | $W_p$ | T | $C_t$ | $R_d$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $M_k$ | 0 | 4 | 3 | 0 | 3 | 3 | 3 | 1 | 2 | 3 | 4 | 1 |
| $F_t$ | 4 | 0 | 3 | 0 | 3 | 3 | 3 | 1 | 3 | 3 | 3 | 0 |
| $L_t$ | 1 | 1 | 0 | 0 | 3 | 0 | 4 | 0 | 0 | 2 | 3 | 2 |
| $P_t$ | 4 | 4 | 3 | 0 | 1 | 3 | 3 | 0 | 1 | 3 | 4 | 0 |
| $D_d$ | 1 | 1 | 3 | 1 | 0 | 0 | 4 | 3 | 0 | 1 | 3 | 4 |
| $E_c$ | 3 | 3 | 0 | 4 | 0 | 0 | 0 | 2 | 0 | 1 | 4 | 0 |
| E | 1 | 1 | 2 | 0 | 1 | 0 | 0 | 0 | 1 | 4 | 3 | 2 |
| $T_t$ | 4 | 4 | 3 | 0 | 1 | 2 | 3 | 0 | 1 | 2 | 3 | 0 |
| $W_p$ | 3 | 3 | 2 | 1 | 0 | 3 | 1 | 4 | 0 | 3 | 3 | 0 |
| T | 1 | 1 | 1 | 0 | 1 | 0 | 4 | 0 | 0 | 0 | 3 | 2 |
| $C_t$ | 4 | 4 | 3 | 3 | 1 | 1 | 2 | 1 | 3 | 3 | 0 | 1 |
| $R_d$ | 0 | 0 | 3 | 0 | 4 | 1 | 3 | 0 | 0 | 3 | 3 | 0 |

Table 8.9 Total relation matrix

| | $M_k$ | $F_t$ | $L_t$ | $P_t$ | $D_d$ | $E_c$ | E | $T_t$ | $W_p$ | T | $C_t$ | $R_d$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $M_k$ | **0.3174** | **0.4464** | **0.4275** | 0.1262 | **0.3443** | **0.2794** | **0.4891** | 0.1808 | 0.2398 | **0.4652** | **0.5682** | 0.2232 |
| $F_t$ | **0.4395** | **0.3105** | **0.4159** | 0.1217 | **0.3332** | **0.2772** | **0.4757** | 0.1812 | 0.2655 | **0.4538** | **0.5265** | 0.1848 |
| $L_t$ | 0.1987 | 0.1987 | 0.1914 | 0.0640 | 0.2470 | 0.0872 | **0.3650** | 0.0753 | 0.0939 | **0.2818** | **0.3458** | 0.1929 |
| $P_t$ | **0.4565** | **0.4565** | **0.4255** | 0.1244 | **0.2789** | **0.2882** | **0.4859** | 0.1388 | 0.2128 | **0.4685** | **0.5712** | 0.1816 |
| $D_d$ | 0.2611 | 0.2611 | **0.3578** | 0.1149 | 0.1953 | 0.1254 | **0.4376** | 0.1956 | 0.1235 | **0.3184** | **0.4270** | **0.2851** |
| $E_c$ | **0.3680** | **0.3680** | 0.2572 | 0.2358 | 0.1834 | 0.1588 | **0.2926** | 0.1724 | 0.1460 | **0.3146** | **0.4674** | 0.1221 |
| E | 0.1933 | 0.1933 | 0.2447 | 0.0607 | 0.1711 | 0.0874 | 0.2173 | 0.0703 | 0.1226 | **0.3332** | **0.3317** | 0.1778 |
| $T_t$ | **0.4195** | **0.4195** | **0.3928** | 0.1057 | 0.2558 | 0.2339 | **0.4460** | 0.1237 | 0.1941 | **0.3955** | **0.4892** | 0.1630 |
| $W_p$ | **0.4071** | **0.4071** | **0.3633** | 0.1479 | 0.2174 | **0.2796** | **0.3831** | 0.2654 | 0.1604 | **0.4300** | **0.4992** | 0.1529 |
| T | 0.1738 | 0.1738 | 0.1946 | 0.0538 | 0.1561 | 0.0756 | **0.3222** | 0.0593 | 0.0821 | 0.1812 | **0.3045** | 0.1666 |
| $C_t$ | **0.4569** | **0.4569** | **0.4328** | 0.2152 | **0.2839** | 0.2306 | **0.4621** | 0.1768 | **0.2765** | **0.4728** | **0.4421** | 0.2137 |
| $R_d$ | 0.1660 | 0.1660 | **0.2918** | 0.0695 | **0.2792** | 0.1149 | **0.3386** | 0.0778 | 0.0876 | **0.3109** | **0.3499** | 0.1302 |

Table 8.10 Calculation of prominence vector and relation vector

| | Diagram Notations | D | R | D+R | D-R |
|---|---|---|---|---|---|
| $M_k$ | C1 | 4.1076 | 3.8578 | 7.9654 | 0.2498 |
| $F_t$ | C2 | 3.9853 | 3.8578 | 7.8431 | 0.1275 |
| $L_t$ | C3 | 2.3418 | 3.9952 | 6.3370 | -1.6534 |
| $P_t$ | C4 | 4.0887 | 1.4397 | 5.5284 | 2.6490 |
| $D_d$ | C5 | 3.1026 | 2.9455 | 6.0481 | 0.1571 |
| $E_c$ | C6 | 3.0865 | 2.2382 | 5.3247 | 0.8483 |
| E | C7 | 2.2034 | 4.7154 | 6.9188 | -2.5120 |
| $T_t$ | C8 | 3.6387 | 1.7174 | 5.3561 | 1.9213 |
| $W_p$ | C9 | 3.7134 | 2.0048 | 5.7182 | 1.7086 |
| T | C10 | 1.9436 | 4.4260 | 6.3696 | -2.4824 |
| $C_t$ | C11 | 4.1204 | 5.3226 | 9.4430 | -1.2022 |
| $R_d$ | C12 | 2.3824 | 2.1939 | 4.5763 | 0.1885 |

Estimate the threshold value ($\alpha$=0.2689) of the total relation matrix. Then, compare all the matrix values with it and marked bold those values whose value is greater than threshold values. In the DEMATEL method, values with the highest prominence vector and relation vector are the most influential criteria. Completion time (C11) and processing time (C4) are the most influential criteria identified from the causal diagram as shown in Fig. 8.1.

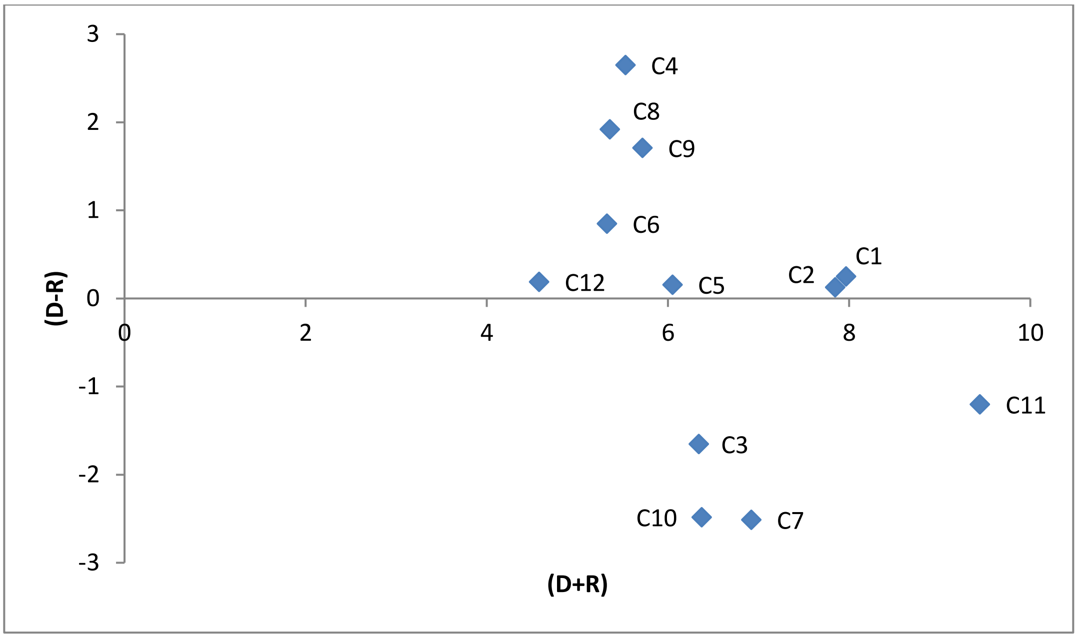

Fig. 8.1 Causal diagram

# Chapter 9

# Results and Analysis

## 9.1 Results and discussion (CASE STUDY-1)

Steps 1 and 2 are common in TOPSIS and MOORA methodology which give the same value of decision matrix and normalized decision matrix as given in Tables 3 and 4 respectively. In this study, equal weightage is given to all the criteria. Thus, the weighted normalized decision matrix for Crankcase Cover Material Selection is the same as the normalized decision matrix. For the calculation of ranking of the alternatives using the TOPSIS technique, separation distances of alternatives ($S^+ \& S^-$) from the positive ideal and negative ideal solution is calculated using Eq. (6) and Eq. (7). Based on these separation distance values, the relative closeness of each alternative to the ideal solution $C_i$ is determined using Eq. (8). The final ranking using the TOPSIS methodology ($\mathrm{A}_3 > \mathrm{A}_2 > \mathrm{A}_4 > \mathrm{A}_1 > \mathrm{A}_5 > \mathrm{A}_6$) is obtained using the decreasing order of these $C_i$ values. The performance score obtained for each alternative via the TOPSIS technique are 58.7%, 58%, 55.7%, 45.5%, 45.4%, and 39.7%. For the calculation of ranking of alternatives using the MOORA methodology, first $\sum_{\mathrm{j}=1}^{\mathrm{q}} \mathrm{x}_{\mathrm{ij}}^*$ value is obtained by adding weighted normalized values of six beneficial criteria which are brinell hardness, yield strength, % elongation, ultimate tensile strength, young's modulus, and fatigue strength. Similarly, $\sum_{\mathrm{j}=\mathrm{q}+1}^{\mathrm{n}} \mathrm{x}_{\mathrm{ij}}^*$ represents the material cost which is a non-beneficial criterion in this study. The final ranking of crankcase cover ($\mathrm{A}_3 > \mathrm{A}_5 > \mathrm{A}_2 > \mathrm{A}_4 > \mathrm{A}_1 > \mathrm{A}_6$) is decided by the overall performance score which is represented by $y_i^*$. Since the number of beneficial criteria is more than the number of non-beneficial criteria, so the overall performance score becomes positive. The final ranking of crankcase cover using the reference point approach is $\mathrm{A}_3 = \mathrm{A}_2 > \mathrm{A}_1 > \mathrm{A}_4 > \mathrm{A}_6 > \mathrm{A}_5$. PROMETHEE approach shows the final ranking $\mathrm{A}_5 > \mathrm{A}_3 > \mathrm{A}_4 > \mathrm{A}_2 > \mathrm{A}_1 > \mathrm{A}_6$. All the above approaches except PROMETHEE represents the aluminum alloy A380 ($A_3$) is the best material for crankcase cover. Fig. 9.1 shows the final ranking of alternatives using the TOPSIS, MOORA, reference point approach, and PROMETHEE. The final ranking of alternatives obtained using these approaches are shown in Table 9.1 to Table 9.4.

Table 9.1 Ranking of the alternatives using TOPSIS method

| Alternatives | $S^+$ | $S^-$ | $C_i$ | Ranking |
|---|---|---|---|---|
| $A_1$ | 0.3189 | 0.2668 | 0.4555 | 4 |
| $A_2$ | 0.2880 | 0.3979 | 0.5802 | 2 |
| $A_3$ | 0.2860 | 0.4076 | 0.5876 | 1 |
| $A_4$ | 0.3149 | 0.3973 | 0.5578 | 3 |
| $A_5$ | 0.3943 | 0.3286 | 0.4546 | 5 |
| $A_6$ | 0.3677 | 0.2421 | 0.3970 | 6 |

Table 9.2 Ranking of the alternatives using MOORA method

| Alternatives | $\sum_{j=1}^{q} x_{ij}^*$ | $\sum_{j=q+1}^{n} x_{ij}^*$ | $y_i^*$ | Ranking |
|---|---|---|---|---|
| A1 | 2.311 | 0.387 | 1.924 | 5 |
| A2 | 2.464 | 0.384 | 2.080 | 3 |
| A3 | 2.473 | 0.352 | 2.121 | 1 |
| A4 | 2.436 | 0.384 | 2.052 | 4 |
| A5 | 2.534 | 0.448 | 2.086 | 2 |
| A6 | 2.242 | 0.480 | 1.762 | 6 |

Table 9.3 Ranking of alternatives using reference point approach

| Sl. No. | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $P_i$ | Rank |
|---|---|---|---|---|---|---|---|---|---|
| $A_1$ | 0.213 | 0.176 | 0.141 | 0.028 | 0.056 | 0.021 | 0.035 | 0.213 | 2 |
| $A_2$ | 0.189 | 0.206 | 0.000 | 0.009 | 0.056 | 0.021 | 0.032 | 0.206 | 1 |
| $A_3$ | 0.189 | 0.206 | 0.000 | 0.000 | 0.056 | 0.021 | 0.000 | 0.206 | 1 |
| $A_4$ | 0.213 | 0.222 | 0.000 | 0.019 | 0.056 | 0.000 | 0.032 | 0.222 | 3 |
| $A_5$ | 0.000 | 0.000 | 0.382 | 0.009 | 0.000 | 0.021 | 0.096 | 0.382 | 5 |
| $A_6$ | 0.189 | 0.239 | 0.141 | 0.037 | 0.056 | 0.042 | 0.128 | 0.239 | 4 |

Table 9.4 Ranking of alternatives using PROMETHEE

| Alternatives | $\phi^+(s)$ | $\phi^-(s)$ | $\phi(s)$ | Ranking |
|---|---|---|---|---|
| A1 | 0.6148 | 1.4100 | 0.7952 | 5 |
| A2 | 1.0941 | 0.7758 | 0.3182 | 4 |
| A3 | 1.5941 | 0.6758 | 0.9182 | 2 |
| A4 | 1.3724 | 0.9691 | 0.4033 | 3 |
| A5 | 3.2629 | 1.4412 | 1.8218 | 1 |
| A6 | 0.1675 | 2.8339 | 2.6664 | 6 |

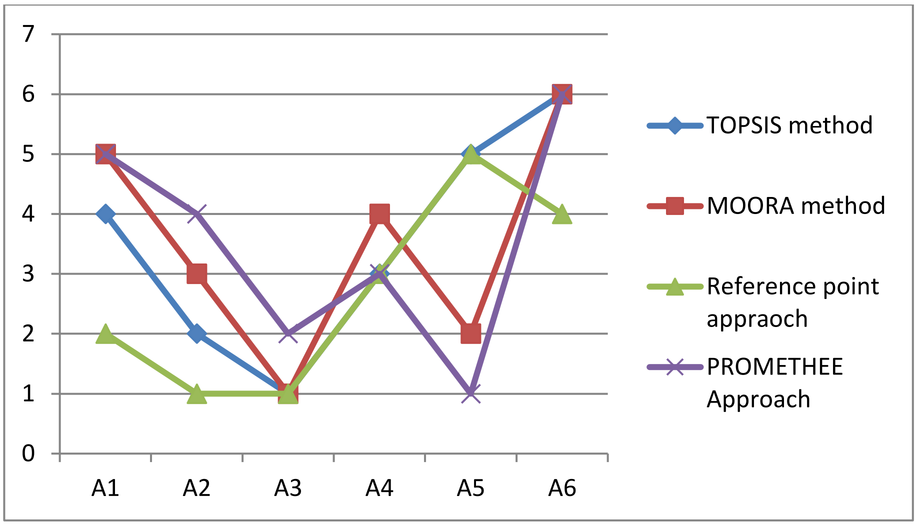


Fig. 9.1 Rankings of the alternatives for material selection

This study proposed the seven-step procedure for the material selection of crankcase cover using the TOPSIS methodology. Results of TOPSIS methodology concluded that the aluminum alloy A380 (A3) is the best material for the two-wheeler crankcase cover in the automobile industry. This result is validated by the MOORA and reference point approach with greater accuracy.

MOORA approach is very simple and easy to implement as compared to the other MCDM approaches. MOORA approach does not give accurate results when large numbers of qualitative attributes are present.

Limitations of this type of study are uncertainty in the decision-making process arises due to uncertainties in the input data and it is also difficult to show the performance of most alternatives by single numerical data. TOPSIS technique does not consider the correlation of the attributes. The proposed integrated model is a simple, easy to implement, and efficient tool for the decision-makers. This novel TOPSIS-PROMETHEE-MOORA method can also be utilized for other material selection problems in the automobile industry. The results obtained in this study are valuable for all automobile industries and research organizations. This study can be further extended by applying other remaining MCDM approaches.

**9.2 Results and discussion (Case Study-2)**

Table 9.5 shows the part sequence obtained from various dispatching rules. This table also describes the parameters optimized by different dispatching rules. Table 9.6 describes the dispatching rule-based priority rule summary for crankcase cover prioritization. Figure 16 shows the priority rule chart. Based on Table 9.6 and Fig. 9.2 to Fig. 9.6, different results can be concluded.

Table 9.5 Part Sequence obtained from various dispatching rules

| Dispatching rule | Part sequence | Parameters minimized |
|---|---|---|
| EDD | K38 → 206G → KTE → KWPG | Maximum lateness and tardiness |
| SPT | 206G → K38 → KTE → KWPG | Average flow time |
| CR | K38 → 206G → KTE → KWPG | Conditional mean tardiness |
| LPT | KWPG → KTE → K38 → 206G | Average hours early |
| WSPT | 206G → KTE → KWPG → K38 | Mean flow time and mean finish time |
| COVERT | K38 → 206G → KWPG → KTE | Average conditional tardiness |
| Hodgson's Algorithm | K38 → 206G → KTE → KWPG | No. of tardy Jobs |

Table 9.6 Priority rule summary

| Rule | Mean flow time | Weighted mean flow time | Mean tardi-ness | Mean lateness | Maximum lateness | Average hours Early | No. of tardy Jobs |
|---|---|---|---|---|---|---|---|
| EDD | 13.25 | 10.87 | 0.00 | -7.50 | -12.50 | 10.25 | 0.00 |
| SPT | 12.87 | 16.23 | 0.00 | -7.87 | -12.50 | 11.12 | 0.00 |
| CR | 13.00 | 16.17 | 0.00 | -7.00 | -10.50 | 9.75 | 0.00 |
| LPT | 16.00 | 15.92 | 3.25 | -4.75 | -22.00 | 8.00 | 2.00 |
| WSPT | 13.625 | 15.08 | 2.12 | -7.12 | -16.00 | 10.37 | 1.00 |
| COVERT | 13.75 | 16.77 | 0.00 | -7.00 | -16.50 | 10.25 | 0.00 |

Among all priority rules, the SPT approach minimizes average flow time but sometimes it increases the inventory cost also. The critical ratio approach provides a balanced schedule having a moderate value of average flow time and due date. Critical ratio priorities are effective for conditional mean tardiness. EDD approach provides better customer satisfaction because it delivers the product to the customer on time, and it minimizes the weighted mean flow time also. In our study, we have shifted our production system from the WSPT approach scheduling to the EDD scheduling approach. EDD scheduling approach minimizes the mean flow time by 2.75%, weighted mean flow time by 27.91%, and maximum lateness by 21.87%. From overall this study, the best part sequence K38→206G→KTE→KWPG is obtained from the EDD rule which helps us in achieving on-time delivery and customer satisfaction. The limitation of the research is that these dispatching rules generally provide low-quality solutions because of lack of flexibility, so they should be used with some mathematical or simulation models to obtain high-quality solutions [125]. This study can be further extended by applying other remaining advanced dispatching rule approaches.

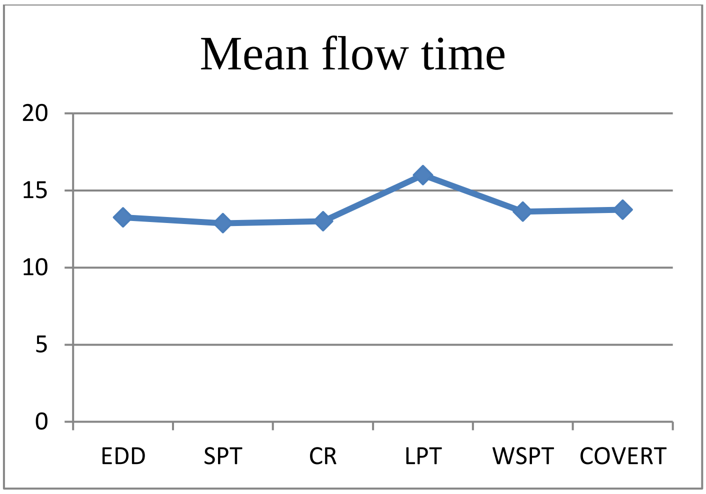


Fig. 9.2 Variation of mean flow time

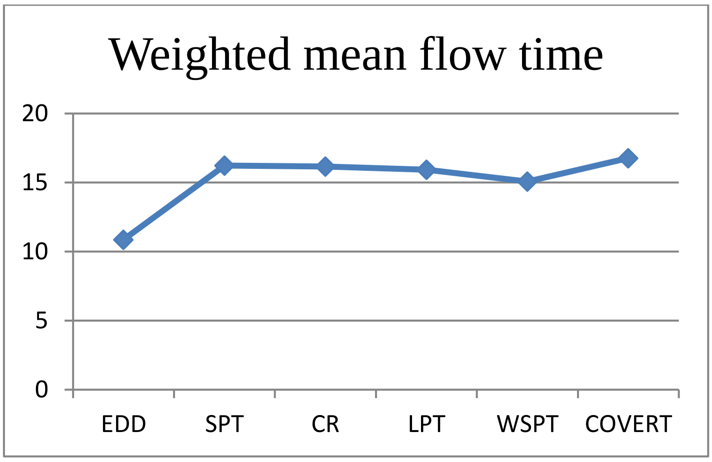


Fig. 9.3 Variation of weighted mean flow time

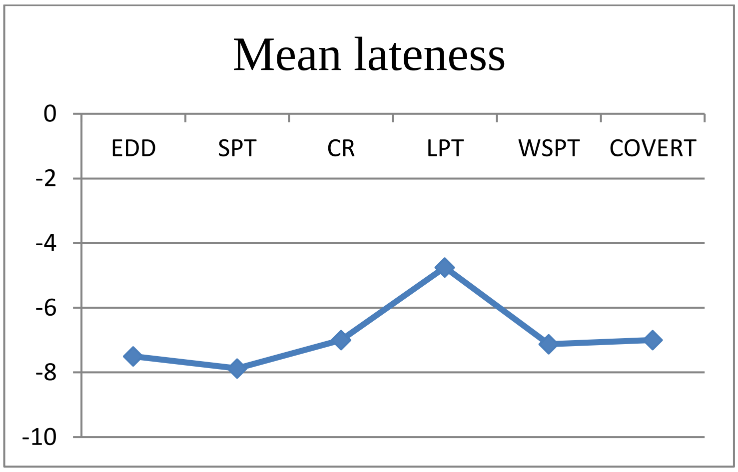


Fig. 9.4 Variation of mean lateness

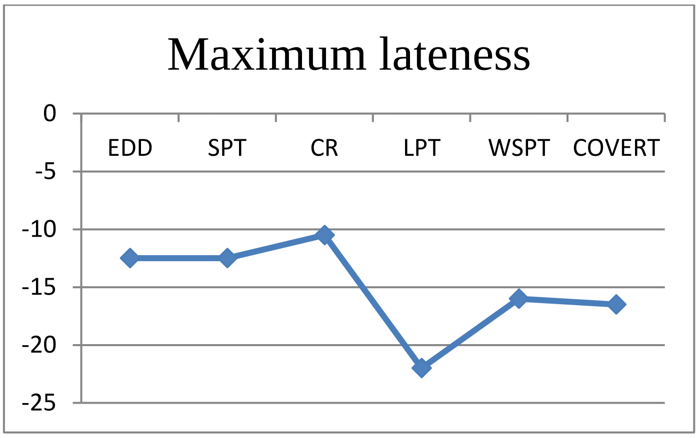


Fig. 9.5 Variation of maximum lateness

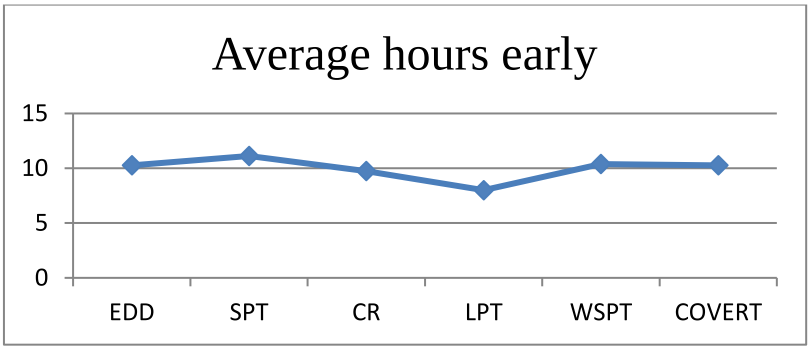


Fig. 9.6 Variation of average hours early

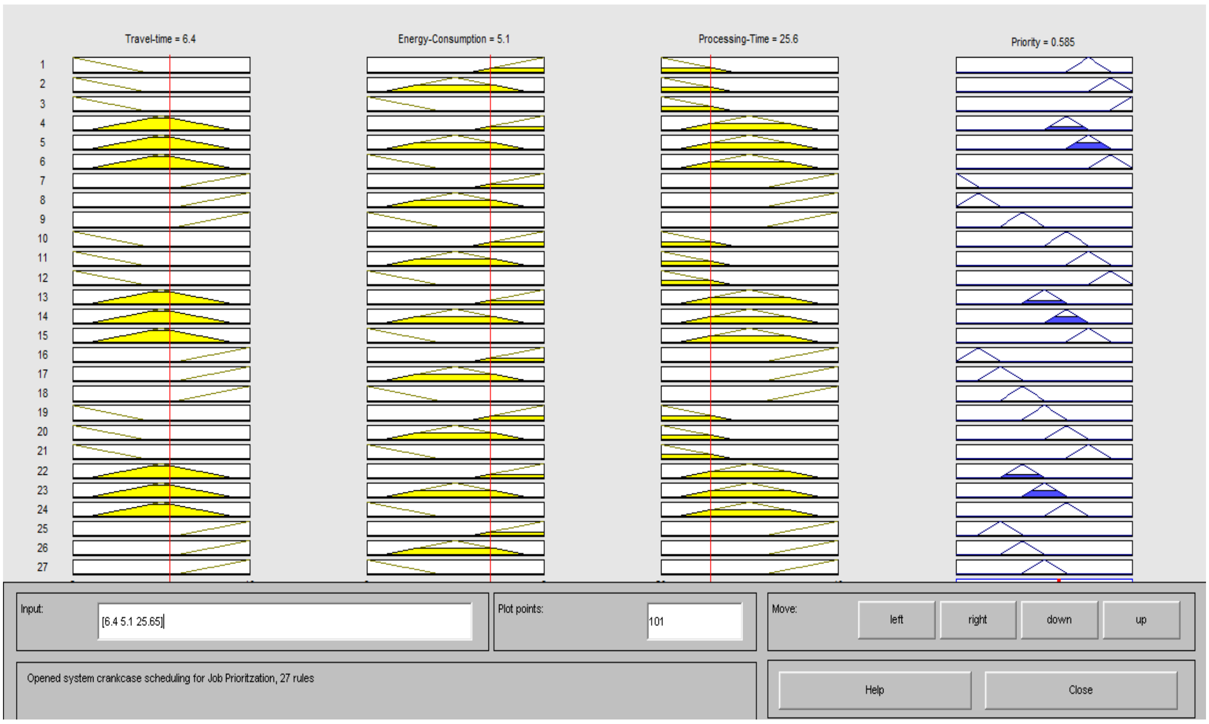


Fig. 9.7 Rule viewer window for crankcase cover prioritization

## 9.3 Results and discussion (Case Study-3)

Rule viewer is a platform of the fuzzy graphical tool in which inputs can be varied for the corresponding outputs. Rule viewer for crankcase cover prioritization is shown in Fig. 9.7.

*9.3.1 Impacts of all inputs on job prioritization and route selection*

The Surface Viewer is another fuzzy graphical tool that examines the output surface of a fuzzy scheduling system for any one or two inputs. The Surface viewer for crankcase cover prioritization is shown in Fig. 9.8 to Fig. 9.10 and for route selection of crankcase cover is shown in Fig. 9.11 to Fig. 9.13.

Fig. 9.8 shows higher priority values of job prioritization for low values of energy consumption and travel time. This diagram also shows that energy consumption has an inverse relation with the priority whereas the priority is high for low values of travel time, and it remains constant for a particular range and then suddenly decreases for the high value of travel time. In Fig. 9.9, we can observe the moderate values of priority for high values for travel time and processing time and high values of priority for low values of travel time and processing time. Travel time and processing time have an almost similar impact on priority. Fig. 9.10 depicts the impacts of processing time and energy consumption on priority and this variation is like Fig. 9.8. Fig. 9.11 and Fig. 9.12 describe the scheduling parameter's impact on the route selection. Travel time and WIQ effects on the priority show a similar variation with processing time and WIQ on the priority. Fig. 9.9 depicts the high values of route selection priority on the low values of processing time and travel time and moderate values of priority on the high values of processing time and travel time.

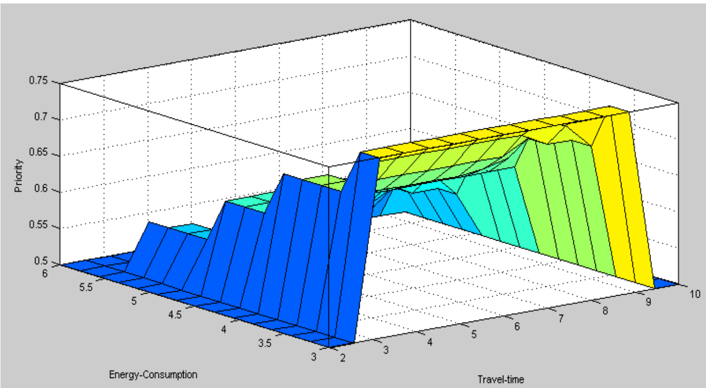


Fig. 9.8 Impact of energy consumption and travel time on job prioritization

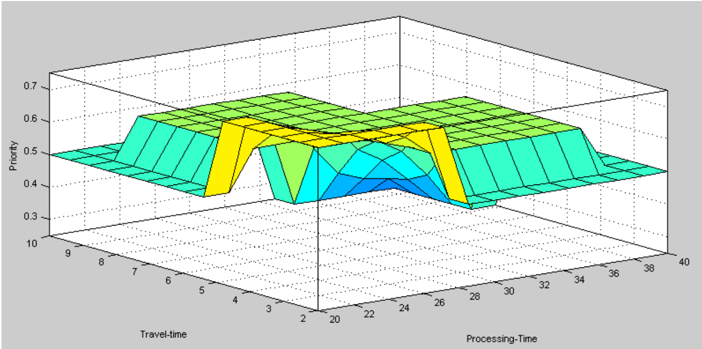


Fig. 9.9 Impact of travel time and processing time on job prioritization

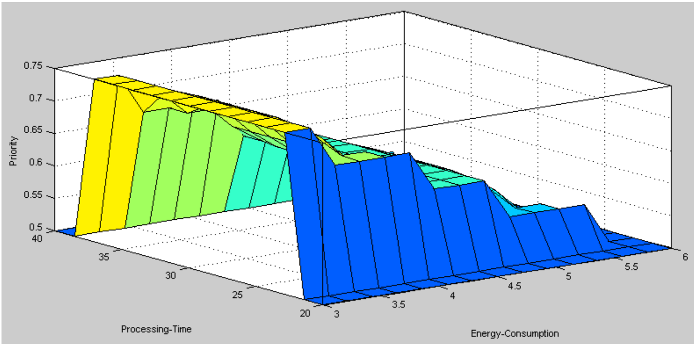


Fig. 9.10 Impact of processing time and energy consumption on job prioritization

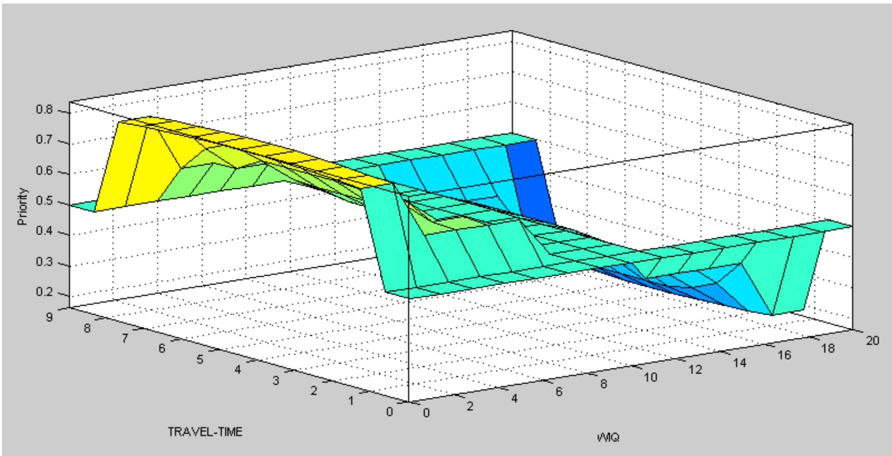


Fig. 9.11 Impact of travel time and WIQ on crankcase cover route selection

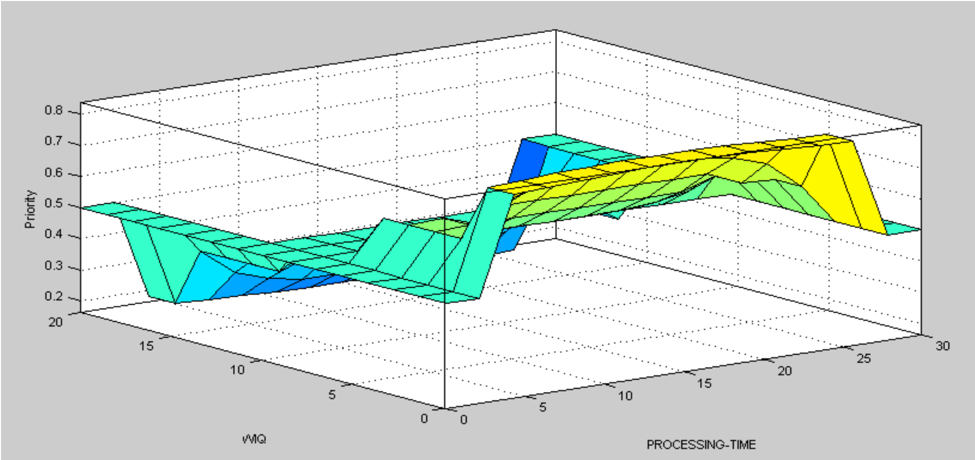


Fig. 9.12 Impact of processing time and WIQ on crankcase cover route selection

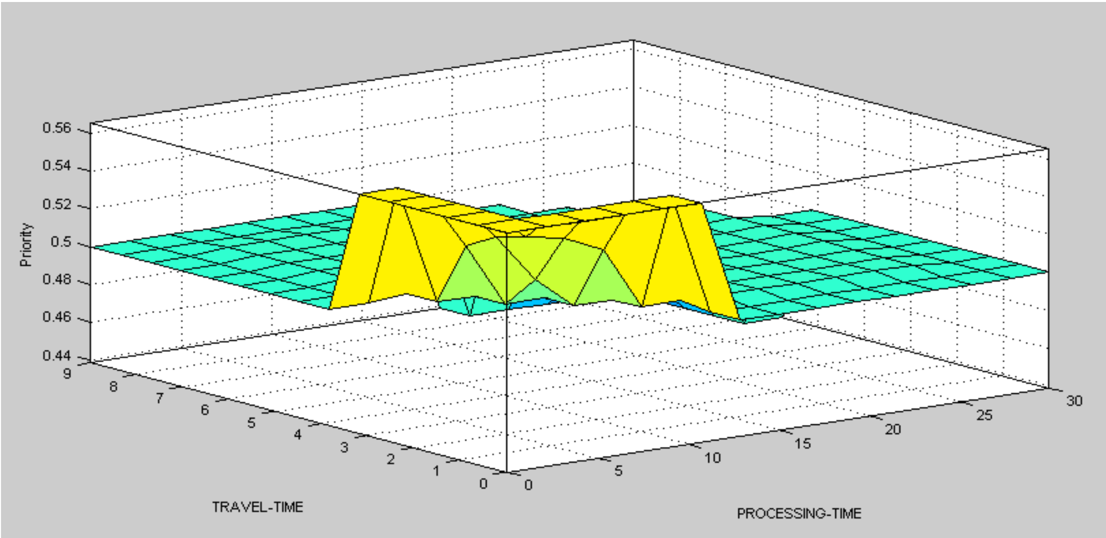


Fig. 9.13 Impact of processing time and travel time on crankcase cover route selection

*9.3.2 Route Priority for all Jobs using FLS*

Route priority of four crankcase cover obtained by a fuzzy logic system is given in Table 9.7

Table 9.7 Crankcase cover priority using fuzzy logic approach

| Route (M/C sequence) | KWPG | K38 | 206G | KTE |
|---|---|---|---|---|
| DCM-MF-DM-VMC-BM-PS | 0.585 | 0.625 | 0.553 | 0.516 |
| DCM-CF-DM-VMC-BM-PS | 0.514 | 0.563 | 0.5 | 0.469 |
| DCM-VMC-DM-VMC-BM-PS | 0.553 | 0.606 | 0.48 | 0.165 |

*9.3.3 Results obtained using Fuzzy Set Approach*

This approach is based on the calculation of membership function values. Based on the maximum final membership function values, route selection is done which is shown in

Table 9.8. The final sequence obtained by the fuzzy logic system and fuzzy set approach is shown in Table 9.9

Table 9.8 Crankcase cover route selection using the fuzzy set approach

| Crankcase Cover | $u_j(i)_{max}$ |
|---|---|
| KWPG | 0.657 |
| K38 | 0.619 |
| 206G | 0.695 |
| KTE | 0.738 |

Table 9.9 Final sequence obtained by fuzzy logic system and fuzzy set approach

| Final sequence obtained by fuzzy logic approach in MATLAB | | Final sequence obtained by fuzzy set approach | |
|---|---|---|---|
| Crankcase cover | Optimum Route (M/C sequence) | Crankcase cover | Optimum Route (M/C sequence) |
| KWPG | DCM-MF-DM-VMC-BM-PS | KWPG | **DCM-MF-DM-VMC-BM-PS**<br>DCM-CF-DM-VMC-BM-PS |
| K38 | DCM-MF-DM-VMC-BM-PS | K38 | **DCM-MF-DM-VMC-BM-PS**<br>DCM-CF-DM-VMC-BM-PS |
| 206G | DCM-MF-DM-VMC-BM-PS | 206G | **DCM-MF-DM-VMC-BM-PS**<br>DCM-CF-DM-VMC-BM-PS |
| KTE | DCM-MF-DM-VMC-BM-PS | KTE | **DCM-MF-DM-VMC-BM-PS** |

For KWPG, K38, and 206G, maximum final membership values for both routes (DCM-MF-DM-VMC-BM-PS, DCM-CF-DM-VMC-BM-PS) are approximately the same. So, both sequences are shown as optimum routes in Table 9.9. Some of the sequences are shown in bold because these are the same sequences that we get using a fuzzy logic approach in MATLAB which is verifying our result.

All maximum priority value is obtained corresponding to the machine sequence (DCM-MF-DM-VMC-BM-PS). Results show the industry must use manual fatling operation rather than CNC or VMC machine for energy-efficient scheduling. Job priority sequence obtained by both fuzzy techniques for four crankcase cover problem= {K38, KWPG, 206G, KTE}.

This study considered the fuzzy logic system for solving the energy-efficient crankcase cover process scheduling problem under uncertain processing times. With the help of the fuzzy logic system in MATLAB, we had done the job prioritization and route selection of crankcase cover manufacturing. The fuzzy rule table is generated for this prioritization based on the different linguistic inputs. Using the fuzzy rule table, the Mamdani fuzzy scheduling system was also developed. This scheduling system provides the trade-off between energy consumption and makespan. Finally, an optimized schedule is obtained using FLS and their results are further validated by the fuzzy set approach. These results are valuable for production engineers and supervisors in all automotive industries.

As future research, another metaheuristic approach like a genetic algorithm or particle swarm optimization can also be applied to this same problem with variable setup time and dynamic uncertainty.

## 9.4 Results and discussion (Case Study-4)

There are various ways to eliminate this bottleneck such as increasing the interarrival time of source1, decreasing the setup time/processing time or adding some more machines in production line. The most preferable method for line balancing is adding more machines in production lines. Since the bottleneck is created before VMC machine, So, add one more VMC machine in production line as shown in Fig. 7.4. After removing this bottleneck, the production line efficiency becomes 97.29%. The increase in throughput value after eliminating bottleneck is also shown in Fig. 7.5.

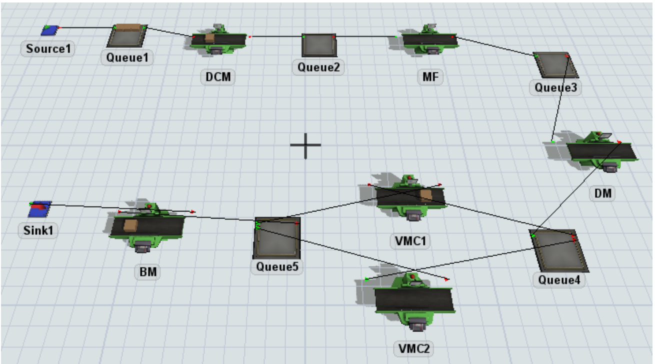


Fig. 9.14 Simulation model after removing bottleneck

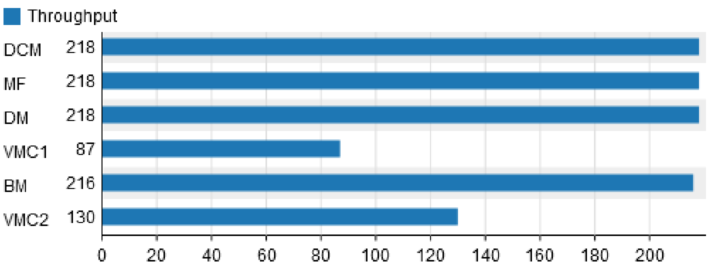


Fig. 9.15 Throughput after removing bottleneck

## 9.5 Results and discussion (Case Study-5)

### *9.5.1 Results using the Fuzzy TOPSIS approach*

$S^+$,$S^-$ and $C_j$ values are calculated using Eq. (6-8). Based on $C_j$ values, priority values are given. Table 9.10 shows the Priority Matrix Based on Closeness Coefficient Values. The most important SPs obtained is makespan and the least important SPs is work in process.

Table 9.10 Priority matrix based on closeness coefficient values

| | $S^+$ | $S^-$ | $C_j$ | Priority |
|---|---|---|---|---|
| $M_k$ | 2.876 | 0.116 | 0.961 | 1 |
| $F_t$ | 0.394 | 2.781 | 0.124 | 11 |
| $L_t$ | 1.577 | 1.964 | 0.445 | 8 |
| $P_t$ | 2.643 | 0.36 | 0.880 | 3 |
| $D_d$ | 2.758 | 0.244 | 0.918 | 2 |
| $E_c$ | 2.09 | 1.094 | 0.656 | 6 |
| E | 1.182 | 2.357 | 0.333 | 9 |
| $T_t$ | 2.566 | 0.36 | 0.876 | 4 |
| $W_p$ | 0 | 2.991 | 0 | 12 |
| T | 2.385 | 0.617 | 0.794 | 5 |
| $C_t$ | 1.795 | 1.571 | 0.533 | 7 |
| $R_d$ | 0.788 | 2.569 | 0.234 | 10 |

*9.5.2 Results using DEMATEL approach*

Optimum Scheduling plays a major role in the effective manufacturing system. This scheduling can only be done by identifying the scheduling parameters. This study provides the methodology of identifying and prioritizing the twelve SPs for automotive part manufacturing. The most important four SPs identified for optimum scheduling using fuzzy TOPSIS are makespan, due date, processing time, and travel time. The least important SPs identified using fuzzy TOPSIS are work in process, flow time, and release date. Cause criteria factors are more crucial than the effect criteria factors. So, all industries and research organizations must give more attention to these factors because cause criteria group improvement has a significant effect on the improvement of the effect criteria group. Results reveal that the completion time and processing time are the most influential criteria in optimum scheduling. This study is useful for all automotive part manufacturers as well as automobile-based research organizations. This study is based on the automobile crankcase cover with five-point linguistic scale.

For further research, the fuzzy VIKOR, and fuzzy PROMETHEE can be applied, and comparison analysis can be done for the same problem. Future research can be carried out by taking any other automotive part with five or more linguistic scales and for a more generalized scheduling model, the number of experts can also be increased.

# Chapter 10

# Conclusions and Future Scope

## 10.1 Conclusions

There is a total of five case studies that we have conducted; results have been summarized as follows.

- Case study 1 is related to the material selection of crankcase cover, in which MCDM techniques have been used to find out the best material for crankcase cover based on some beneficial and non-beneficial criteria. Results of TOPSIS methodology concluded that the aluminum alloy A380 is the best material for the two-wheeler crankcase cover in the automobile industry. This result is validated by the MOORA and reference point approach with greater accuracy.
- Case study 2 deals with the dispatching rule-based single machine static scheduling of crankcase cover manufacturing. In this study, we have shifted our production system from the WSPT approach scheduling to the EDD scheduling approach. EDD scheduling approach minimizes the mean flow time by 2.75%, weighted mean flow time by 27.91%, and maximum lateness by 21.87%. From overall this study, the best part sequence K38→206G→KTE→KWPG is obtained from the EDD rule which helps us in achieving on-time delivery and customer satisfaction.
- Case study 3 considers the development of an energy-efficient fuzzy scheduling system for crankcase covers manufacturing. The optimum route obtained from this system is DCM-MF-DM-VMC-BM-PS and DCM-CF-DM-VMC-BM-PS. Results also show that the industry must use manual fatling operation rather than CNC or VMC machine for energy-efficient scheduling. Job priority sequence obtained by both fuzzy techniques for four crankcase cover problem= {K38, KWPG, 206G, KTE}. This study considered the fuzzy logic system for solving the energy-efficient crankcase cover process scheduling problem under uncertain processing times. This scheduling system provides the trade-off between energy consumption and makespan. These results are valuable for production engineers and supervisors in all automotive industries.
- Modelling and simulation of crankcase cover manufacturing in the automobile industry is done in case study 4. The results indicate that by eliminating the bottleneck in the production line, it increases the line efficiency as well as the production throughput. Initially production line efficiency is just 51.8 % when

bottleneck is present at queue 4. By adding one more vertical milling centre in the production line, we eliminated this queue 4 bottleneck and increases not only throughput but also line efficiency to 97.29%.

- Prioritizing scheduling parameters in the automotive industry using fuzzy TOPSIS-DEMATEL model is conducted in case study 5. The most important four SPs identified for optimum scheduling using fuzzy TOPSIS are makespan, due date, processing time, and travel time. The least important SPs identified using fuzzy TOPSIS are work in process, flow time, and release date. Makespan (C1), flow time (C2), processing time (C4), due date (C5), energy consumption (C6), travel time (C8), work in process (C9), and release date (C12) are classified into cause criteria group, whereas effect criteria group consists of lateness (C3), earliness (C7), tardiness (C10), and completion time (C11). Cause criteria factors are more crucial than the effect criteria factors. So, all industries and research organizations must give more attention to these factors because cause criteria group improvement has a significant effect on the improvement of the effect criteria group.
- This thesis titled “Prioritization and Efficient Route Selection in Automotive Parts Manufacturing” has been studied in detail and after effective five case studies, it is concluded that the developed scheduling system which uses optimum scheduling parameters provides the trade-off between energy consumption and makespan. Identification of best material through MCDM model also enhances this production system performance and developed simulation model enhances the quality of solutions obtained through dispatching rule based static scheduling. These results are valuable for the production engineers and the supervisors in all automotive industries.

## 10.2 Recommendations for industries

- Case study 1 recommends using aluminium alloy A380 material for the manufacturing of crankcase cover because it optimizes the seven attributes (Brinell hardness, yield strength, % elongation, young’s modulus, ultimate tensile strength, fatigue strength, and material cost) using integrated MCDM model. Case study 2 recommends shifting the production system from WSPT approach to EDD approach to minimizes the mean flow time, weighted mean flow time and maximum lateness. If industry wants to expand its plant, case study 4 model based on modelling and simulation will help in eliminating the bottleneck and optimizes the throughput and line efficiency whereas, case study 5 recommend using this machine sequence DCM-MF-DM-VMC-BM-PS and job sequence {K38, KWPG, 206G, KTE} for optimizing the energy consumption and makespan.

### 10.3 Future Scope

Following issues can be addressed in the future course of research.

- In this thesis, chapter 4 includes the comparative analysis using integrated TOPSIS -PROMETHEE-MOORA model for the material selection of crankcase cover. In all these MCDM techniques, if we changed the input values then result of ranking can also varies. So, to check the robustness of a MCDM model in the presence of uncertainty, we need sensitivity analysis. This analysis helps us in finding the effects of uncertainties w.r.t the criterion on the selection problems. This MCDM based comparative analysis model work can be extended with sensitivity analysis. This material selection work is focused on seven attributes only. However, this work can be extended with some other attributes such as corrosion rate, machinability, fracture toughness, izod impact, and charpy impact etc. In this material selection work, equal weights of attributes have been considered. The weights can be calculated with the MCDM approaches such as fuzzy AHP or entropy method etc.
- In case study 2, the dispatching rule-based single machine static scheduling of crankcase cover manufacturing is done. This work can be extended for hybrid flow shop with the hybrid dispatching rules such as SST+EDD, SST+SPT, SST+CR, and SST+MST or hybridization of dispatching rules and genetic algorithm used for advanced complex problems. Case study 3 considers the development of an energy-efficient fuzzy scheduling system for crankcase covers manufacturing. Type 1 fuzzy system deals with the fixed membership function, whereas type 2 fuzzy systems also incorporate the uncertainty in membership function. So, this study is extended with type 2 fuzzy for the measurement of the uncertainty.

# References


1. Abbasi M, Hosnavi R, Tabrizi B (2013) Application of Fuzzy DEMATEL in Risks Evaluation of Knowledge-Based Networks. J Optim 2013:1–7. doi: 10.1155/2013/913467

2. Abd K, Abhary K, Marian R (2016) Multi-objective optimisation of dynamic scheduling in robotic flexible assembly cells via fuzzy-based Taguchi approach. Comput Ind Eng 99:250–259. doi: 10.1016/j.cie.2016.07.028

3. Abdelaziz EA, Saidur R, Mekhilef S (2011) A review on energy saving strategies in industrial sector. Renew Sustain Energy Rev 15:150–168. doi: 10.1016/j.rser.2010.09.003

4. Abdullah S, Abdolrazzagh-Nezhad M (2014) Fuzzy job-shop scheduling problems: A review. Inf Sci (Ny) 278:380–407. doi: 10.1016/j.ins.2014.03.060

5. Aghelinejad MM, Ouazene Y, Yalaoui A (2018) Production scheduling optimisation with machine state and time-dependent energy costs. Int J Prod Res 56:5558–5575. doi: 10.1080/00207543.2017.1414969

6. Agnetis A, Aloulou MA, Kovalyov MY (2017) Integrated production scheduling and batch delivery with fixed departure times and inventory holding costs. Int J Prod Res 55:6193–6206. doi: 10.1080/00207543.2017.1346323

7. Agrawal R, Pattanaik LN, Kumar S (2012) Scheduling of a flexible job-shop using a multi-objective genetic algorithm. J Adv Manag Res 9:178–188. doi: 10.1108/09727981211271922

8. Agrawal S, Singh RK, Murtaza Q (2016) Prioritizing critical success factors for reverse logistics implementation using fuzzy-TOPSIS methodology. J Ind Eng Int 12:15–27. doi: 10.1007/s40092-015-0124-8

9. Ahmed I, Sultana I, Paul SK, Azeem A (2013) Employee performance evaluation: A fuzzy approach. Int J Product Perform Manag 62:718–734. doi: 10.1108/IJPPM-01-2013-0013

10. Akyol DE, Bayhan GM (2007) A review on evolution of production scheduling with neural networks. Comput Ind Eng 53:95–122. doi: 10.1016/j.cie.2007.04.006

11. Alharkan IM (2005) Algorithms for Sequencing and Scheduling. Riyadha: Industrial Engineering Department, College of Engineering, King Saud University

12. Allahverdi A (2008) Three-machine flowshop scheduling problem to minimize makespan with bounded setup and processing times. J Chinese Inst Ind Eng 25:52–61. doi: 10.1080/10170660809509072

13. Allahverdi A (2015) The third comprehensive survey on scheduling problems with setup times/costs. Eur J Oper Res 246:345–378. doi: 10.1016/j.ejor.2015.04.004

14. Aly MF, Attia HA, Mohammed AM (2013) Integrated Fuzzy ( GMM ) -TOPSIS Model for Best Design Concept and Material Selection Process. Int J Innov Res Sci Eng Technol 2:6464–6486

15. Amiri MP (2010) Project selection for oil-fields development by using the AHP and fuzzy TOPSIS methods. Expert Syst Appl 37:6218–6224. doi: 10.1016/j.eswa.2010.02.103

16. Amirian H, Sahraeian R (2017) Solving a grey project selection scheduling using a simulated shuffled frog leaping algorithm. Comput Ind Eng 107:141–149. doi: 10.1016/j.cie.2017.03.018

17. Anojkumar L, Ilangkumaran M, Sasirekha V (2014) Comparative analysis of MCDM methods for pipe material selection in sugar industry. Expert Syst Appl 41:2964–2980. doi: 10.1016/j.eswa.2013.10.028

18. Artigues C, Lopez P, Haït A (2013) The energy scheduling problem: Industrial case-study and constraint propagation techniques. Int J Prod Econ 143:13–23. doi: 10.1016/j.ijpe.2010.09.030

19. Ashby MF, Cebon D, Salvo L (2004) Selection strategies for materials and processes. Mater Des 25:51–67. doi: 10.1016/S0261-3069(03)00159-6

20. Ashrafzadeh M (2012) Application of fuzzy TOPSIS method for the selection of Warehouse Location : A Case Study. Interdiscip J Contemp Res Bus 3:655–671

21. Atan MO, Selim Akturk M (2008) Single CNC machine scheduling with controllable processing times and multiple due dates. Int J Prod Res 46:6087–6111. doi: 10.1080/00207540701262913

22. Athawale VM, Kumar R, Chakraborty S (2011) Decision making for material selection using the UTA method. Int J Adv Manuf Technol 57:11–22. doi: 10.1007/s00170-011-3293-7

23. Azab A, Karam A, Eltawil A, Azab A, Karam A (2019) A simulation-based optimization approach for external trucks appointment scheduling in container terminals scheduling in container terminals. Int J Model Simul 1–18. doi: 10.1080/02286203.2019.1615261

24. Babaei H, Karimpour J, Hadidi A (2017) Applying Hybrid Fuzzy Multi-Criteria Decision-Making Approach to Find the Best Ranking for the Soft Constraint Weights of Lecturers in UCTP. Int J Fuzzy Syst. doi: 10.1007/s40815-017-0296-z

25. Badri MA, Hollingsworth J (1993) A Simulation Model for Scheduling in the Emergency Room. In: International journal of operations & production management. pp 13–24

26. Bagchi S (2016) Distributed scheduling with probabilistic and fuzzy classifications of processes. Futur Gener Comput Syst 62:1–16. doi: 10.1016/j.future.2016.03.001

27. Ballestín F, Leus R (2008) Meta-heuristics for stable scheduling on a single machine. Comput Oper Res 35:2175–2192. doi: 10.1016/j.cor.2006.10.017

28. Behnamian J (2015) Survey on fuzzy shop scheduling. Fuzzy Optim Decis Mak. doi: 10.1007/s10700-015-9225-5

29. Bellman RE, Zadeh LA (1970) Decision-Making in a Fuzzy Environment. Manage Sci 17(4):B-141-B-164

30. Benmansour R, Allaoui H, Artiba A (2012) Stochastic single machine scheduling with random common due date. Int J Prod Res 50:3560–3571. doi: 10.1080/00207543.2012.671589

31. Bennell JA, Mesgarpour M, Potts CN (2017) Dynamic scheduling of aircraft landings. Eur J Oper Res 258:315–327. doi: 10.1016/j.ejor.2016.08.015

32. Bhowmik C, Gangwar S, Bhowmik S (2018) Optimum Selection of Energy-Efficient Material : A MCDM-Based Distance Approach Evaluation of Mixed Data. In: K. Ray et al. (eds.), Soft Computing Applications, Studies in Computational Intelligence 761. Springer Singapore, pp 59–79

33. Bjorklund S, Yamani N, Lloyd T (2004) Simulation Software for Real Time Forecasting as an Operational Support. In: Second World Conference on POM and 15th Annual POM Conference, Cancun, Mexico. pp 1–30

34. Bonvoisin J, Thiede S, Brissaud D, Herrmann C (2013) An implemented framework to estimate manufacturing-related energy consumption in product design. Int J Comput Integr Manuf 26:866–880. doi: 10.1080/0951192X.2013.799782

35. Bozorgi A, Pedram MM, Yousefi GR (2016) Unit Maintenance Scheduling: A robust model, based on fuzzy cost factors and peak loads. Int J Electr Power Energy Syst 79:142–149. doi: 10.1016/j.ijepes.2015.11.062

36. Brans JP, Vincke P (1985) A Preference Ranking Organisation Method: (The PROMETHEE Method for Multiple Criteria Decision-Making). Manage Sci 31:647–656

37. BRANS JP, VINCKE P, MARESCHAL B (1986) How to select and how to rank projects: The PROMETHEE method. Eur J Oper Res 24:228–238

38. Brauers WK (2004) Optimization methods for a stakeholder society. A revolution in economic thinking by multiobjective optimization. Kluwer Academic Publishers, Boston

39. Brauers WKM, Zavadskas EK (2006) The MOORA method and its application to privatization in a transition economy. Control Cybern 35:445–469

40. Bruzzone AAG, Anghinolfi D, Paolucci M, Tonelli F (2012) Energy-aware scheduling for improving manufacturing process sustainability: A mathematical model for flexible flow shops. CIRP Ann - Manuf Technol 61:459–462. doi: 10.1016/j.cirp.2012.03.084

41. Büyüközkan G, Çifçi G (2012) A combined fuzzy AHP and fuzzy TOPSIS based strategic analysis of electronic service quality in healthcare industry. Expert Syst Appl 39:2341–2354. doi: 10.1016/j.eswa.2011.08.061

42. Castro PM, Harjunkoski I, Grossmann IE (2011) Optimal scheduling of continuous plants with energy constraints. Comput Chem Eng 35:372–387. doi: 10.1016/j.compchemeng.2010.05.008

43. Cesaret B, Oğuz C, Sibel Salman F (2012) A tabu search algorithm for order acceptance and scheduling. Comput Oper Res 39:1197–1205. doi: 10.1016/j.cor.2010.09.018

44. Chakrabortty RK, Sarker RA, Essam DL (2017) Resource constrained project scheduling with uncertain activity durations. Comput Ind Eng 112:537–550. doi: 10.1016/j.cie.2016.12.040

45. Chakraborty S (2011) Applications of the MOORA method for decision making in manufacturing environment. Int J Adv Manuf Technol 54:1155–1166. doi: 10.1007/s00170-010-2972-0

46. Chakraborty S, Chatterjee P (2013) Selection of materials using multi-criteria decision-making methods with minimum data. Decis Sci Lett 2:135–148. doi: 10.5267/j.dsl.2013.03.005

47. Chan FTS, Chan HK, Kazerooni A (2003) Real time fuzzy scheduling rules in FMS. J Intell Manuf 14:341–350. doi: 10.1023/A:1024601826420

48. Chan HK, Chung SH, Lim MK (2013) Recent research trend of economic-lot scheduling problems. J Manuf Technol Manag 24:465–482. doi: 10.1108/17410381311318936

49. Chanas S (2001) Minimizing maximum lateness in a single machine scheduling problem with fuzzy processing times and fuzzy due dates. Eng Appl Artif Intell 14:377–386. doi: 10.1016/S0952-1976(01)00011-2

50. Chandika S, Asokan R (2011) Design and analysis of piezoactuated micropump for fuel delivery in automobiles. J Sci Ind Res (India) 70:448–454

51. Chatterjee P (2013) Gear Material Selection using Complex Proportional Assessment and Additive Ratio Assessment-based Approaches : A Comparative Study. Int J Mater Sci Eng 1:104–111. doi: 10.12720/ijmse.1.2.104-111

52. Chatterjee P, Chakraborty S (2012) Material selection using preferential ranking methods. Mater Des 35:384–393. doi: 10.1016/j.matdes.2011.09.027

53. Chauhan A, Singh A, Jharkharia S (2018) An interpretive structural modeling ( ISM ) and decision-making trail and evaluation laboratory ( DEMATEL ) method approach for the analysis of barriers of waste recycling in India. J Air Waste Manage Assoc 68:100–110. doi: 10.1080/10962247.2016.1249441

54. Chaurasia SN, Singh A (2017) Hybrid evolutionary approaches for the single machine order acceptance and scheduling problem. Appl Soft Comput J 52:725–747. doi: 10.1016/j.asoc.2016.09.051

55. Chawla S (2014) Developing Fuzzy Scheduling System for Jobs Prioritization & Route Selection of Jobs in FMS. Int J Sci Res 3:1310–1313

56. Chawla S, Agrawal S, Singari RM (2019) Integrated Topsis-Moora Model for Prioritization of New Bike Selection. In: Prasad A., Gupta S., Tyagi R. (eds) Advances in Engineering Design. Lecture Notes in Mechanical Engineering. Springer, Singapore. pp 755–765

57. Chen C (2000) Extensions of the TOPSIS for group decision-making under fuzzy environment. Fuzzy Sets Syst 114:1–9

58. Chen G, Zhang L, Arinez J, Biller S (2013) Energy-efficient production systems

through schedule-based operations. IEEE Trans Autom Sci Eng 10:27–37. doi: 10.1109/TASE.2012.2202226

59. Chen I (2016) Journal of Air Transport Management A combined MCDM model based on DEMATEL and ANP for the selection of airline service quality improvement criteria : A study based on the Taiwanese airline industry. J Air Transp Manag 57:7–18. doi: 10.1016/j.jairtraman.2016.07.004

60. Cheng HC, Chan DYK (2011) Simulation optimization of part input sequence in a flexible manufacturing system. In: Winter Simulation Conference. pp 2374–2382

61. Cheng HC, Güçdemir H, Selim H, González-neira EM, Montoya-torres JR, Caballero- JP, Zou B, Kan Z, Kessel D, Jeon J, Jung J, Oh E, Kim C, Ka C, Lin Y, Wai T, Ling C, Yeung WK, Azab A, Karam A, Eltawil A, Azab A, Karam A, Badri MA, Hollingsworth J, Bjorklund S, Yamani N, Lloyd T (1993) Simulation Software for Real Time Forecasting as an Operational Support. In: Second World Conference on POM and 15th Annual POM Conference, Cancun, Mexico. Taylor & Francis, pp 1–30

62. Cheng TCE, Ding Q, Lin BMT (2004) A concise survey of scheduling with time-dependent processing times. Eur J Oper Res 152:1–13. doi: 10.1016/S0377-2217(02)00909-8

63. Cheng TCE, Lin BMT (2017) Demonstrating Johnson's algorithm via resource-constrained scheduling. Int J Prod Res 55:3326–3330. doi: 10.1080/00207543.2017.1314040

64. Chiang TC, Fu LC (2007) Using dispatching rules for job shop scheduling with due date-based objectives. Int J Prod Res 45:3245–3262. doi: 10.1080/00207540600786715

65. Chiou CY, Hsu CW, Chen HC (2011) Using DEMATEL to Explore a Casual and Effect Model of Sustainable Supplier Selection. 2011 IEEE Int Summer Conf Asia Pacific Bus Innov Technol Manag Dalian 240–244. doi: 10.1109/APBITM.2011.5996331.

66. Choi SH, Yang FY (2005) Quick value-setting algorithms for the longest path problem of job-shop scheduling. J Manuf Technol Manag 16:956–972. doi: 10.1108/17410380510627906

67. Choi YC (2016) Dispatching Rule-based Scheduling Algorithms in a Single Machine with Sequence-dependent Setup Times and Energy Requirements. Procedia CIRP 41:135–140. doi: 10.1016/j.procir.2015.12.109

68. Choi YC, Xirouchakis P (2014) A production planning in highly automated manufacturing system considering multiple process plans with different energy requirements. Int J Adv Manuf Technol 70:853–867. doi: 10.1007/s00170-013-5306-1

69. Chu J, Li W, Yang H, Yu S (2017) An approach for prioritizing key factors affecting air travel experience based on grey theory and DEMATEL. In: Proceedings of the 23rd International Conference on Automation & Computing, University of Huddersfield, Huddersfield, UK. pp 7–8

70. Chu T-C (2002) Selecting Plant Location via a Fuzzy TOPSIS Approach. Int J Adv Manuf Technol 20:859–864

71. Chu T, Lin Y (2003) A Fuzzy TOPSIS Method for Robot Selection. Int J Adv Manuf Technol 21:284–290

72. Çinar SM (2022) Developing hierarchical fuzzy logic controllers to improve the energy efficiency and cutting rate stabilization of natural stone block-cutting machines. J Clean Prod 355:article 131799. doi: 10.1016/j.jclepro.2022.131799

73. Coudert T, Grabot B, Archimède B (2002) Production/maintenance cooperative scheduling using multi-agents and fuzzy logic. Int J Prod Res 40:4611–4632. doi: 10.1080/00207540210159545

74. Croce F Della, Scatamacchia R (2020) The Longest Processing Time rule for identical parallel machines revisited. J Sched 23:163–176. doi: 10.1007/s10951-018-0597-6

75. Dagdeviren M (2008) Decision making in equipment selection : an integrated approach with AHP and PROMETHEE. J Intell Manuf 19:397–406. doi: 10.1007/s10845-008-0091-7

76. Dai M, Tang D, Giret A, Salido MA, Li WD (2013) Energy efficient scheduling for a flexible flow shop using an improved genetic-simulated annealing algorithm. Robot Comput Manuf 29 418–429. doi: 10.1016/j.rcim.2013.04.001

77. Daneshvar B, Babek R, Eko T (2014) Supplier selection using integrated fuzzy TOPSIS and MCGP : a case study. Procedia - Soc Behav Sci 116:3957–3970. doi: 10.1016/j.sbspro.2014.01.874

78. Denkena B, Dittrich MA, Winter F (2017) Competence-based Personnel Scheduling through Production Data. Procedia CIRP 63:265–270. doi: 10.1016/j.procir.2017.03.114

79. Devapriya P, Ferrell W, Geismar N (2017) Integrated production and distribution scheduling with a perishable product. Eur J Oper Res 259:906–916. doi: 10.1016/j.ejor.2016.09.019

80. Dhingra A, Chandna P (2010) Multi-objective flow shop scheduling using hybrid simulated annealing. Meas Bus Excell 14:30–41. doi: 10.1108/13683041011074191

81. Dorry MHFZF (2017) A Hybrid Fuzzy PSO Algorithm for Solving Steelmaking-Continuous Casting Scheduling Problem. Int J Fuzzy Syst. doi: 10.1007/s40815-017-0331-0

82. Dubois D, Fargier H, Fortemps P (2003) Fuzzy scheduling: Modelling flexible constraints vs. coping with incomplete knowledge. Eur J Oper Res 147:231–252. doi: 10.1016/S0377-2217(02)00558-1

83. Dubois D, Fargier H, Prade H (1995) Fuzzy constraints in job-shop scheduling. J Intell Manuf 6:215–234. doi: 10.1007/BF00128646

84. Duflou JR, Sutherland JW, Dornfeld D, Herrmann C, Jeswiet J, Kara S, Hauschild M, Kellens K (2012) Towards energy and resource efficient manufacturing: A

processes and systems approach. CIRP Ann - Manuf Technol 61:587–609. doi: 10.1016/j.cirp.2012.05.002

85. Dursun M, Arslan Ö (2018) An Integrated Decision Framework for Material Selection Procedure : A Case Study in a Detergent Manufacturer. Symmetry (Basel) 10:1–14. doi: 10.3390/sym10110657

86. Edwards KL (2005) Selecting materials for optimum use in engineering components. Mater Des 26:469–473. doi: 10.1016/j.matdes.2004.07.004

87. Enab TA, Bondok NE (2013) Material selection in the design of the tibia tray component of cemented artificial knee using finite element method. Mater Des 44:454–460. doi: 10.1016/j.matdes.2012.08.017

88. Ertugrul İ, Karakasoglu N (2008) Comparison of fuzzy AHP and fuzzy TOPSIS methods for facility location selection. Int J Adv Manuf Technol 39:783–795. doi: 10.1007/s00170-007-1249-8

89. Escamilla J, Salido MA, Giret A, Barber F (2016) A metaheuristic technique for energy-efficiency in job-shop scheduling. Knowl Eng Rev 31:475–485. doi: 10.1017/S026988891600031X

90. Faddel S, Al-Awami AT, Abido MA (2017) Fuzzy Optimization for the Operation of Electric Vehicle Parking Lots. Electr Power Syst Res 145:166–174. doi: 10.1016/j.epsr.2017.01.008

91. Fang K, Uhan N, Zhao F, Sutherland JW (2011) A new approach to scheduling in manufacturing for power consumption and carbon footprint reduction. J Manuf Syst 30:234–240. doi: 10.1016/j.jmsy.2011.08.004

92. Fang K, Uhan NA, Zhao F, Sutherland JW (2013) Flow shop scheduling with peak power consumption constraints. Ann Oper Res 206:115–145. doi: 10.1007/s10479-012-1294-z

93. Fang KT, Lin BMT (2013) Parallel-machine scheduling to minimize tardiness penalty and power cost. Comput Ind Eng 64:224–234. doi: 10.1016/j.cie.2012.10.002

94. Fattahi P, Fallahi A (2010) Dynamic scheduling in flexible job shop systems by considering simultaneously efficiency and stability. CIRP J Manuf Sci Technol 2:114–123. doi: 10.1016/j.cirpj.2009.10.001

95. Fattahi P, Jolai F, Arkat J (2009) Flexible job shop scheduling with overlapping in operations. Appl. Math. Model. 33:3076–3087

96. Fauadi M, Azimi NZ, Anuar NI, Ali MM, Sued MK, Ramlan S (2018) Simulation Approach for Logistical Planning in a Warehouse : A Review. Orient J Comput Sci Technol 11:201–208

97. Fayazbakhsh K, Abedian A, Manshadi BD, Khabbaz RS (2009) Introducing a novel method for materials selection in mechanical design using Z -transformation in statistics for normalization of material properties. Mater Des 30:4396–4404. doi: 10.1016/j.matdes.2009.04.004

98. Feng C et al. (2022) Minimizing the energy consumption of hole machining integrating the optimization of tool path and cutting parameters on CNC machines. Int J Adv Manuf Technol 121:215–228. doi: 10.1007/s00170-022-09343-5

99. Findik F, Turan K (2012) Materials selection for lighter wagon design with a weighted property index method. Mater Des 37:470–477. doi: 10.1016/j.matdes.2012.01.016

100. Fliege J, Kaparis K, Khosravi B (2012) Operations research in the space industry. Eur J Oper Res 217:233–240. doi: 10.1016/j.ejor.2011.06.035

101. Fortemps P (1997) Jobshop scheduling with imprecise durations: A fuzzy approach. IEEE Trans Fuzzy Syst 5:557–569. doi: 10.1109/91.649907

102. Freed T, Doerr KH, Chang T (2007) In-house development of scheduling decision support systems: Case study for scheduling semiconductor device test operations. Int J Prod Res 45:5075–5093. doi: 10.1080/00207540600818351

103. Fu F (2014) Integrated scheduling and batch ordering for construction project. Appl Math Model 38:784–797. doi: 10.1016/j.apm.2013.07.017

104. Fu LL, Aloulou MA, Triki C (2017) Integrated production scheduling and vehicle routing problem with job splitting and delivery time windows. Int J Prod Res 55:5942–5957. doi: 10.1080/00207543.2017.1308572

105. Fujimoto T (2014) The Long Tail of the Auto Industry Life Cycle. J Prod Innov Manag 31:8–16. doi: 10.1111/jpim.12076

106. Gahm C, Denz F, Dirr M, Tuma A (2016) Energy-efficient scheduling in manufacturing companies: A review and research framework. Eur J Oper Res 248:744–757. doi: 10.1016/j.ejor.2015.07.017

107. Garcia-Santiago CA, Del Ser J, Upton C, Quilligan F, Gil-Lopez S, Salcedo-Sanz S (2015) A random-key encoded harmony search approach for energy-efficient production scheduling with shared resources. Eng Optim 47:1481–1496. doi: 10.1080/0305215X.2014.971778

108. Geiger CD, Uzsoy R, Aytu H (2006) Rapid modeling and discovery of priority dispatching rules: an autonomous learning approach. J Sched 9:7–34. doi: 10.1097/00001721-200404000-00010

109. Geyik F, Elibal K (2017) A linguistic approach to non-identical parallel processor scheduling with fuzzy processing times. Appl Soft Comput J 55:63–71. doi: 10.1016/j.asoc.2016.12.029

110. Gong G, Deng Q, Gong X, Liu W, Ren Q (2018) A new double flexible job-shop scheduling problem integrating processing time, green production, and human factor indicators. J Clean Prod 174:560–576. doi: 10.1016/j.jclepro.2017.10.188

111. Gong L, Zou B, Kan Z (2019) Modeling and Optimization for Automobile Mixed Assembly Line in Industry 4.0. J Control Sci Eng 2019:1–10

112. Gong X, De Pessemier T, Joseph W, Martens L (2015) An energy-cost-aware scheduling methodology for sustainable Manufacturing. Procedia CIRP 29:185–190.

doi: 10.1016/j.procir.2015.01.041

113. Gong X, Van Der Wee M, De Pessemier T, Verbrugge S, Colle D, Martens L, Joseph W (2017) Energy- and Labor-aware Production Scheduling for Sustainable Manufacturing: A Case Study on Plastic Bottle Manufacturing. Procedia CIRP 61:387–392. doi: 10.1016/j.procir.2016.11.136

114. Grabot B, Geneste L (2007) Dispatching rules in scheduling : a fuzzy approach. Int J Prod Res 32:903–915. doi: 10.1080/00207549408956978

115. Guha D, Chakraborty D (2010) A new approach to fuzzy distance measure and similarity measure between two generalized fuzzy numbers. Appl Soft Comput J 10:90–99. doi: 10.1016/j.asoc.2009.06.009

116. Gupta N (2011) Material selection for thin-film solar cells using multiple attribute decision making approach. Mater Des 32:1667–1671. doi: 10.1016/j.matdes.2010.10.002

117. Hatagar S, Halase S V (2015) Three Input – One Output Fuzzy logic control of Washing Machine. Int J Sci Res Eng Technol 4:57–62

118. He Y, Li Y, Wu T, Sutherland JW (2015) An energy-responsive optimization method for machine tool selection and operation sequence in flexible machining job shops. J Clean Prod 87:245–254. doi: 10.1016/j.jclepro.2014.10.006

119. He Y, Liu B, Zhang X, Gao H, Liu X (2012) A modeling method of task-oriented energy consumption for machining manufacturing system. J Clean Prod 23:167–174. doi: 10.1016/j.jclepro.2011.10.033

120. Herrmann C, Thiede S, Kara S, Hesselbach J (2011) Energy oriented simulation of manufacturing systems - Concept and application. CIRP Ann - Manuf Technol 60:45–48. doi: 10.1016/j.cirp.2011.03.127

121. Herroelen W, Leus R (2005) Project scheduling under uncertainty: Survey and research potentials. Eur J Oper Res 165:289–306. doi: 10.1016/j.ejor.2004.04.002

122. Hock Soon T, de Souza School R (1997) Intelligent simulation-based scheduling of workcells: an approach. Integr Manuf Syst 8:6–23. doi: 10.1108/09576069710158754

123. Hosseini Ezzabadi J, Dehghani Saryazdi M, Mostafaeipour A (2015) Implementing Fuzzy Logic and AHP into the EFQM model for performance improvement: A case study. Appl Soft Comput J 36:165–176. doi: 10.1016/j.asoc.2015.06.051

124. Hsu CY, Kao BR, Ho VL, Lai KR (2016) Agent-based fuzzy constraint-directed negotiation mechanism for distributed job shop scheduling. Eng Appl Artif Intell 53:140–154. doi: 10.1016/j.engappai.2016.04.005

125. Huang J, Süer GA (2015) A dispatching rule-based genetic algorithm for multi-objective job shop scheduling using fuzzy satisfaction levels. Comput Ind Eng 86:29–42. doi: 10.1016/j.cie.2014.12.001

126. Huynh N (2009) Reducing Truck Turn Times at Marine Terminals with Appointment Scheduling. Transp Res Rec J Transp Res Board 47–57. doi:

10.3141/2100-06

127. Ibrahim A, Hosam A (2018) A DEMATEL method in identifying design requirements for mobile environments : students ' perspectives. J Comput High Educ. doi: 10.1007/s12528-018-9176-2

128. Ilangkumaran M, Avenash A, Balakrishnan V., Kumar B, Raja MB (2013) Material selection using hybrid MCDM approach for automobile bumper. Int J Ind Syst Eng 14:20–39

129. Ipek M, Selvi IH, Findik F, Torkul O (2013) An expert system based material selection approach to manufacturing. Mater Des 47:331–340. doi: 10.1016/j.matdes.2012.11.060

130. Ishibuchi H, Murata T (1998) A multi-objective genetic local search algorithm and its application to flowshop scheduling. IEEE Trans Syst Man Cybern Part C Appl Rev 28:392–403. doi: 10.1109/5326.704576

131. Ishibuchi H, Yamamoto N, Misaki S, Tanaka H (1994) Local search algorithms for flow shop scheduling with fuzzy due-dates. Int J Prod Econ 33:53–66. doi: 10.1016/0925-5273(94)90118-X

132. Jafari H, Bateni S, Daneshvar P, Bateni S (2015) Fuzzy Mathematical Modeling Approach for the Nurse Scheduling Problem : A Case Study. Int J Fuzzy Syst. doi: 10.1007/s40815-015-0051-2

133. Jahan A, Bahraminasab M, Edwards KL (2012) A target-based normalization technique for materials selection. Mater Des 35:647–654. doi: 10.1016/j.matdes.2011.09.005

134. Jahan A, Ismail MY, Sapuan SM, Mustapha F (2010) Material screening and choosing methods – A review. Mater Des 31:696–705. doi: 10.1016/j.matdes.2009.08.013

135. Jahan A, Ismail Y, Mustapha F, Mohd S (2010) Material selection based on ordinal data. Mater Des 31:3180–3187. doi: 10.1016/j.matdes.2010.02.024

136. Jajimoggala S, Karri RR (2013) Decision making model for material selection using a hybrid MCDM technique. Int J Appl Decis Sci 6:144–159

137. Jarernram J, Samattapapong N Parallel Machine Scheduling using Simulation Software. In: 4th International Conference On Mechanical Engineering and Industrial Automation Held on 23rd-24th March 2018, in Pattaya, Thailand ISBN: 9780998900049

138. Jayaswal P, Verma SN, Wadhwani AK (2010) Application of ANN, Fuzzy Logic and Wavelet Transform in machine fault diagnosis using vibration signal analysis. J Qual Maint Eng 16:190–213. doi: 10.1108/13552511011048922

139. Jeong K-C, Kim Y-D (1998) A real-time scheduling mechanism for a flexible manufacturing system : Using simulation and dispatching rules. Int J Prod Res 36:2609–2626. doi: 10.1080/002075498192733

140. Jiang Z, Zuo L, Mingcheng E (2014) Study on multi-objective flexible job-shop

scheduling problem considering energy consumption. J Ind Eng Manag 7:589–604. doi: 10.3926/jiem.1075

141. Jin Zhao, Bose BK (2002) Evaluation of membership functions for fuzzy logic controlled induction motor drive. IEEE 2002 28th Annu Conf Ind Electron Soc IECON 02 1:229–234. doi: 10.1109/IECON.2002.1187512

142. Jolai F, Ahmad S, Shahanaghi K, Azari M (2011) Integrating fuzzy TOPSIS and multi-period goal programming for purchasing multiple products from multiple suppliers. J Purch Supply Manag 17:42–53. doi: 10.1016/j.pursup.2010.06.004

143. José Palacios J, González-Rodríguez I, Vela CR, Puente J (2017) Robust multiobjective optimisation for fuzzy job shop problems. Appl Soft Comput J 56:604–616. doi: 10.1016/j.asoc.2016.07.004

144. Kamaruddin S, Khan ZA, Siddiquee AN, Wong YS (2013) The impact of variety of orders and different number of workers on production scheduling performance A simulation approach. J Manuf Technol Manag 24:1123–1142. doi: 10.1108/JMTM-12-2010-0083

145. Kara S, Manmek S, Herrmann C (2010) Global manufacturing and the embodied energy of products. CIRP Ann - Manuf Technol 59:29–32. doi: 10.1016/j.cirp.2010.03.004

146. Karande P, Chakraborty S (2012) Application of multi-objective optimization on the basis of ratio analysis ( MOORA ) method for materials selection. Mater Des 37:317–324. doi: 10.1016/j.matdes.2012.01.013

147. Karhi S, Shabtay D (2018) Single machine scheduling to minimise resource consumption cost with a bound on scheduling plus due date assignment penalties. Int J Prod Res 56:3080–3096. doi: 10.1080/00207543.2017.1400708

148. Kelemenis A, Askounis D (2010) A new TOPSIS-based multi-criteria approach to personnel selection. Expert Syst Appl 37:4999–5008. doi: 10.1016/j.eswa.2009.12.013

149. Kesen SE, Sert M (2019) A simulation analysis of a serial line pull system producing orders with various part types and volumes. Int J Model Simul. doi: 10.1080/02286203.2019.1588007

150. Kessel D, Jeon J, Jung J, Oh E, Kim C (2019) Logistical Simulation Modeling for Planning a Soil Remediation Process. Sci Technol Nucl Install 2019:1–13

151. Khabbaz RS, Manshadi BD, Abedian A, Mahmudi R (2009) A simplified fuzzy logic approach for materials selection in mechanical engineering design. Mater Des 30:687–697. doi: 10.1016/j.matdes.2008.05.026

152. Kianfar K, Ghomi SMTF, Karimi B (2009) New dispatching rules to minimize rejection and tardiness costs in a dynamic flexible flow shop. Int J Adv Manuf Technol 45:759–771. doi: 10.1007/s00170-009-2015-x

153. Kim DB, Hwang H, Yoon WC (1995) Developing a dispatching rule for an automated guided vehicle system using a fuzzy multi-criteria decision-making method. Eng Optim 24:39–57. doi: 10.1080/03052159508941182

154. Kim S, Meng C, Son YJ (2017) Simulation-based machine shop operations scheduling system for energy cost reduction. Simul Model Pract Theory 77:68–83. doi: 10.1016/j.simpat.2017.05.007

155. Kim SH, Lee YH (2016) Synchronized production planning and scheduling in semiconductor fabrication. Comput Ind Eng 96:72–85. doi: 10.1016/j.cie.2016.03.019

156. Klir GJ (1997) Fuzzy arithmetic with requisite constraints. Fuzzy Sets Syst 91:165–175. doi: 10.1016/S0165-0114(97)00138-3

157. Knyazeva M, Bozhenyuk A, Rozenberg I (2015) Resource-constrained Project Scheduling Approach under Fuzzy Conditions. Procedia Comput Sci 77:56–64. doi: 10.1016/j.procs.2015.12.359

158. Koller R, Ricardez-Sandoval L (2017) Integration of Design, Control and Scheduling: A Dynamic Optimization Framework for Multi-product Chemical Processes under Disturbances and Uncertainty. Comput Aided Chem Eng 40:2077–2082. doi: 10.1016/B978-0-444-63965-3.50348-2

159. Kousi N, Koukas S, Michalos G, Makris S, Chryssolouris G (2016) Service Oriented Architecture for Dynamic Scheduling of Mobile Robots for Material Supply. Procedia CIRP 55:18–22. doi: 10.1016/j.procir.2016.09.014

160. Krishna LSR, Saketh TSS, Kumar MVS (2015) A Simulation Based Approach for Studying the Effect of Buffers on the Performance of an FMS. Int J Eng Sci Invent 4:5–9

161. Kuo W-H, Yang D-L (2006) Minimizing the total completion time in a single-machine scheduling problem with a time-dependent learning effect. Eur J Oper Res 174:1184–1190. doi: 10.1016/j.apm.2010.11.006

162. Kuroda M, Wang Z (1996) Fuzzy job shop scheduling. Int J Prod Econ 44:45–51. doi: 10.1016/0925-5273(95)00091-7

163. Labib AW, Yuniarto MN (2005) Intelligent real time control of disturbances in manufacturing systems. J Manuf Technol Manag 16:864–889. doi: 10.1108/17410380510627861

164. Lawler EL (1994) Knapsack-Like Scheduling Problems , the Moore-Hodgson Algorithm and the ‘ Tower of Sets ’ Property. 20:91–106

165. Lawrynowicz A (2011) Advanced scheduling with genetic algorithms in supply networks. J Manuf Technol Manag 22:748–769. doi: 10.1108/17410381111149620

166. Lee S, Do Chung B, Jeon HW, Chang J (2017) A dynamic control approach for energy-efficient production scheduling on a single machine under time-varying electricity pricing. J Clean Prod 165:552–563. doi: 10.1016/j.jclepro.2017.07.102

167. Lei D, Guo X (2015) An effective neighborhood search for scheduling in dual-resource constrained interval job shop with environmental objective. Int J Prod Econ 159:296–303. doi: 10.1016/j.ijpe.2014.07.026

168. Li D, Zeng W, Li J (2015) New distance and similarity measures on hesitant fuzzy

sets and their applications in multiple criteria decision making. Eng Appl Artif Intell 40:11–16. doi: 10.1016/j.engappai.2014.12.012

169. Li J, Zeng W, Xie J, Yin Q (2016) Engineering Applications of Arti fi cial Intelligence A new fuzzy regression model based on least absolute deviation $. Eng Appl Artif Intell 52:54–64. doi: 10.1016/j.engappai.2016.02.009

170. Li L, Huang H, Zhao F, Liu Z (2017) Operation scheduling of multi-hydraulic press system for energy consumption reduction. J Clean Prod 165:1407–1419. doi: 10.1016/j.jclepro.2017.07.158

171. Li Y, He Y, Wang Y, Yan P, Liu X (2014) A framework for characterising energy consumption of machining manufacturing systems. Int J Prod Res 52:314–325. doi: 10.1080/00207543.2013.813983

172. Lin CKY, Ling TWC, Yeung WK (2017) Resource Allocation and Outpatient Appointment Scheduling Using Simulation Optimization. J Healthc Eng 2017:1–19

173. Lin Y, Yang Y, Kang J, Yu H (2011) Expert Systems with Applications Using DEMATEL method to explore the core competences and causal effect of the IC design service company : An empirical case study. Expert Syst Appl 38:6262–6268. doi: 10.1016/j.eswa.2010.11.092

174. Litoiu M, Tadei R (2001) Real-time task scheduling with fuzzy deadlines and processing times. Fuzzy Sets Syst 117:35–45

175. Liu GS, Zhou Y, Yang HD (2017) Minimizing energy consumption and tardiness penalty for fuzzy flow shop scheduling with state-dependent setup time. J Clean Prod 147:470–484. doi: 10.1016/j.jclepro.2016.12.044

176. Liu H, Liu L, Wu J (2013) Material selection using an interval 2-tuple linguistic VIKOR method considering subjective and objective weights. Mater Des 52:158–167. doi: 10.1016/j.matdes.2013.05.054

177. Liu HC, Yih Y (2013) A fuzzy-based approach to the liquid crystal injection scheduling problem in a TFT-LCD fab. Int J Prod Res 51:6163–6181. doi: 10.1080/00207543.2013.810820

178. Liu L, Zhou H (2015) Single-machine rescheduling with deterioration and learning effects against the maximum sequence disruption. Int J Syst Sci 46:2640–2658. doi: 10.1080/00207721.2013.876519

179. Liu Y, Dong H, Lohse N, Petrovic S (2016) A multi-objective genetic algorithm for optimisation of energy consumption and shop floor production performance. Int J Prod Econ 179:259–272. doi: 10.1016/j.ijpe.2016.06.019

180. Liu Y, Dong H, Lohse N, Petrovic S, Gindy N (2014) An investigation into minimising total energy consumption and total weighted tardiness in job shops. J Clean Prod 65:87–96. doi: 10.1016/j.jclepro.2013.07.060

181. Liu Y, Lohse N, Petrovic S, Gindy N (2013) An investigation into minimising total energy consumption, total energy cost and total tardiness based on a rolling blackout policy in a job shop. IFIP Adv Inf Commun Technol 397:103–110. doi: 10.1007/978-3-642-40352-1_14

182. Løken E (2007) Use of multicriteria decision analysis methods for energy planning problems. Renew Sustain Energy Rev 11:1584–1595. doi: 10.1016/j.rser.2005.11.005

183. Lowe C, Tedford JD (1997) Fuzzy Production Scheduling for JIT Manufacturing. Intell Autom Soft Comput 3:319–329. doi: 10.1080/10798587.1997.10750711

184. Lu C, Gao L, Li X, Pan Q, Wang Q (2017) Energy-efficient permutation flow shop scheduling problem using a hybrid multi-objective backtracking search algorithm. J Clean Prod 144:228–238. doi: 10.1016/j.jclepro.2017.01.011

185. Lu C, Gao L, Li X, Xiao S (2017) A hybrid multi-objective grey wolf optimizer for dynamic scheduling in a real-world welding industry. Eng Appl Artif Intell 57:61–79. doi: 10.1016/j.engappai.2016.10.013

186. Lu MS, Liu YJ (2011) Dynamic dispatching for a flexible manufacturing system based on fuzzy logic. Int J Adv Manuf Technol 54:1057–1065. doi: 10.1007/s00170-010-2993-8

187. Luo H, Fang J, Huang GQ (2015) Real-time scheduling for hybrid flowshop in ubiquitous manufacturing environment. Comput Ind Eng 84:12–23. doi: 10.1016/j.cie.2014.09.019

188. Mahdevari S, Shahriar K, Esfahanipour A (2014) Human health and safety risks management in underground coal mines using fuzzy TOPSIS. Sci Total Environ 488–489:85–99. doi: 10.1016/j.scitotenv.2014.04.076

189. Maity SR, Chakraborty S (2013) Grinding Wheel Abrasive Material Selection Using Fuzzy TOPSIS Method. Mater Manuf Process 28:408–417. doi: 10.1080/10426914.2012.700159

190. Mansouri SA, Aktas E, Besikci U (2015) Green scheduling of a two-machine flowshop: Trade-off between makespan and energy consumption. Eur J Oper Res 000:1–17. doi: 10.1016/j.ejor.2015.08.064

191. May G, Stahl B, Taisch M, Prabhu V (2015) Multi-objective genetic algorithm for energy-efficient job shop scheduling. Int J Prod Res 53:7071–7089. doi: 10.1080/00207543.2015.1005248

192. Merkert L, Harjunkoski I, Isaksson A, Säynevirta S, Saarela A, Sand G (2015) Scheduling and energy - Industrial challenges and opportunities. Comput Chem Eng 72:183–198. doi: 10.1016/j.compchemeng.2014.05.024

193. Metaxiotis K, Psarras J, Samouilidis E (2003) Integrating fuzzy logic into decision suppport systems: Current research and future prospects. Inf Manag Comput Secur 11:53–59. doi: 10.1108/09685220310468592

194. Metaxiotis KS, Psarras JE, Ergazakis KA (2003) Production scheduling in ERP systems: An AI-based approach to face the gap. Bus Process Manag J 9:190–207. doi: 10.1108/14637150310468416

195. Milani AS, Eskicioglu C, Robles K, Bujun K (2011) Multiple criteria decision making with life cycle assessment for material selection of composites. eXPRESS Polym Lett 5:1062–1074. doi: 10.3144/expresspolymlett.2011.104

196. Mishra A, Tripathi AK (2014) Energy efficient voltage scheduling for multi-core processors with software controlled dynamic voltage scaling. Appl Math Model 38:3456–3466. doi: 10.1016/j.apm.2013.12.009

197. Mishra A, Tripathi AK (2014) Energy efficient voltage scheduling for multi-core processors with software controlled dynamic voltage scaling. Appl Math Model 38:3456–3466. doi: 10.1016/j.apm.2013.12.009

198. Mittler M, Schoemig AK (1999) Comparison of dispatching rules for semiconductor manufacturing using large facility models. In: Winter Simulation Conference. pp 709–713

199. Mohammadi M, Tavakkoli-Moghaddam R, Siadat A, Rahimi Y (2016) A game-based meta-heuristic for a fuzzy bi-objective reliable hub location problem. Eng Appl Artif Intell 50:1–19. doi: 10.1016/j.engappai.2015.12.009

200. Mokhtari H, Hasani A (2017) An energy-efficient multi-objective optimization for flexible job-shop scheduling problem. Comput Chem Eng 104:339–352. doi: 10.1016/j.compchemeng.2017.05.004

201. Mori M, Fujishima M, Inamasu Y, Oda Y (2011) A study on energy efficiency improvement for machine tools. CIRP Ann - Manuf Technol 60:145–148. doi: 10.1016/j.cirp.2011.03.099

202. Mousavi-nasab SH, Sotoudeh-anvai A (2017) A comprehensive MCDM-based approach using TOPSIS, COPRAS and DEA as an auxiliary tool for material selection problems. Mater Des 121:237–253. doi: 10.1016/j.matdes.2017.02.041

203. Mouzon G, Yildirim MB, Twomey J (2007) Operational methods for minimization of energy consumption of manufacturing equipment. Int J Prod Res 45:4247–4271. doi: 10.1080/00207540701450013

204. Muffatto M, Payaro A (2004) Implementation of e-procurement and e-fulfillment processes: A comparison of cases in the motorcycle industry. Int J Prod Econ 89:339–351. doi: 10.1016/S0925-5273(02)00301-8

205. Muhuri PK, Shukla KK (2008) Real-time task scheduling with fuzzy uncertainty in processing times and deadlines. Appl Soft Comput J 8:1–13. doi: 10.1016/j.asoc.2006.06.006

206. Mulliner E, Malys N, Maliene V (2016) Comparative analysis of MCDM methods for the assessment of sustainable housing affordability. Omega 59:146–156. doi: 10.1016/j.omega.2015.05.013

207. Nabipour M, Razaz M, Seifossadat SG, Mortazavi SS (2016) A novel adaptive fuzzy membership function tuning algorithm for robust control of a PV-based Dynamic Voltage Restorer (DVR). Eng Appl Artif Intell 53:155–175. doi: 10.1016/j.engappai.2016.04.007

208. Nanvala H (2011) Use of Fuzzy Logic Approaches in Scheduling of FMS : A Review. Int J Comput Sci Eng 3:1734–1739

209. Nguyen TT, Gordon-Brown L (2012) Constrained fuzzy hierarchical analysis for portfolio selection under higher moments. IEEE Trans Fuzzy Syst 20:666–682. doi:

10.1109/TFUZZ.2011.2181520

210. Nie X, Wang L (2019) Simulation Process Design for Scheduling Mode of Railway Container Terminals based on Flexsim. In: J. Phys.: Conf. Ser. 1176 052012

211. Noryani M, Sapuan SM, Mastura MT (2018) Multi-criteria decision-making tools for material selection of natural fibre composites: A review. J Mech Eng Sci 12:3330–3353

212. Oke SA, Charles-Owaba OE (2006) An approach for evaluating preventive maintenance scheduling cost. Int J Qual Reliab Manag 23:847–879. doi: 10.1108/02656710610679842

213. Oke SA, Charles-Owaba OE (2006) Application of fuzzy logic control model to Gantt charting preventive maintenance scheduling. Int J Qual Reliab Manag 23:441–459. doi: 10.1108/02656710610657620

214. Okokpujie IP, Okonkwo UC, Bolu CA, Ohunakin OS, Agboola MG, Atayero AA (2020) Implementation of multi-criteria decision method for selection of suitable material for development of horizontal wind turbine blade for sustainable energy generation. Heliyon 6:1–10. doi: 10.1016/j.heliyon.2019.e03142

215. Ou J, Zhong X, Wang G (2015) An improved heuristic for parallel machine scheduling with rejection. Eur J Oper Res 241:653–661. doi: 10.1016/j.ejor.2014.09.028

216. Özgüven C, Sungur B (2013) Integer programming models for hierarchical workforce scheduling problems including excess off-days and idle labour times. Appl Math Model 37:9117–9131. doi: 10.1016/j.apm.2013.04.006

217. Pedrycz W (1994) Why triangular membership functions? Fuzzy Sets Syst 64:21–30. doi: 10.1016/0165-0114(94)90003-5

218. Pellegrinelli S, Valente A, Tosatti LM (2015) Energy-efficient distributed part programme for highly automated production systems. Int J Comput Integr Manuf 28:395–407. doi: 10.1080/0951192X.2014.914631

219. Peng Y, Jiang YC (2013) Production process scheduling based on simulation with global optimization strategy: a case study. Inf Technol J 12:983–989

220. Perez-Gonzalez P, Framinan JM (2015) Assessing scheduling policies in a permutation flowshop with common due dates. Int J Prod Res 53:5742–5754. doi: 10.1080/00207543.2014.994077

221. Pfund ME, Fowler JW (2017) Extending the boundaries between scheduling and dispatching: hedging and rescheduling techniques. Int J Prod Res 55:3294–3307. doi: 10.1080/00207543.2017.1306133

222. Phani K, Kumar R, Kamala V, Kumar A (2013) Simulation Of Job Shop Scheduling Problem. Int J Eng Res Technol 2:831–834

223. Pinedo M (1996) Scheduling: Theory, Algorithms, and Systems. IIE Trans 28:695–697. doi: 10.1080/15458830.1996.11770714

224. Pinedo ML (2008) Theory, Algorithms, and Systems. Stern School of Business NewYork University NewYork, NY USA

225. Rai D, Jha GK, Chatterjee P, Chakraborty S (2013) Material Selection in Manufacturing Environment Using Compromise Ranking and Regret Theory-based Compromise Ranking Methods : A Comparative Study. Univers J Mater Sci 1:69–77. doi: 10.13189/ujms.2013.010210

226. Rajabinasab A, Mansour S (2011) Dynamic flexible job shop scheduling with alternative process plans: An agent-based approach. Int J Adv Manuf Technol 54:1091–1107. doi: 10.1007/s00170-010-2986-7

227. Rao R V, Patel BK (2010) A subjective and objective integrated multiple attribute decision making method for material selection. Mater Des 31:4738–4747. doi: 10.1016/j.matdes.2010.05.014

228. Rashid T, Beg I, Muhammad S (2014) Robot selection by using generalized interval-valued fuzzy numbers with TOPSIS. Appl Soft Comput J. doi: 10.1016/j.asoc.2014.04.002

229. Raza SA, Al-Turki UM (2007) A comparative study of heuristic algorithms to solve maintenance scheduling problem. J Qual Maint Eng 13:398–410. doi: 10.1108/13552510710829489

230. Restrepo IM, Balakrishnan S (2008) Fuzzy-based methodology for multi-objective scheduling in a robot-centered flexible manufacturing cell. J Intell Manuf 19:421–432. doi: 10.1007/s10845-008-0093-5

231. Rodammer FA (1989) A Recent Survey of Production Scheduling. IEEE Trans Syst Man, Cybern Syst 18

232. Rodrigues RP, Pinho AF De, Custo D (2019) Application of Hybrid Simulation in production scheduling in job shop systems. Simul Trans ofthe Soc Model Simul Int 1–16. doi: 10.1177/0037549719861724

233. Rommelfanger H (1996) Fuzzy linear programming and applications. Eur J Oper Res 92:512–527

234. Rosat S, Quesnel F, Elhallaoui I, Soumis F (2017) Dynamic penalization of fractional directions in the integral simplex using decomposition: Application to aircrew scheduling. Eur J Oper Res 263:1007–1018. doi: 10.1016/j.ejor.2017.05.047

235. Rostamzadeh R, Sofian S (2011) Prioritizing effective 7Ms to improve production systems performance using fuzzy AHP and fuzzy TOPSIS (case study). Expert Syst Appl 38:5166–5177. doi: 10.1016/j.eswa.2010.10.045

236. Shabtay D, Gaspar N, Kaspi M (2013) A survey on offline scheduling with rejection. J Sched 16:3–28. doi: 10.1007/s10951-012-0303-z

237. Shanian A, Savadogo O (2006) TOPSIS multiple-criteria decision support analysis for material selection of metallic bipolar plates for polymer electrolyte fuel cell. J Power Sources 159:1095–1104. doi: 10.1016/j.jpowsour.2005.12.092

238. Shen XN, Yao X (2015) Mathematical modeling and multi-objective evolutionary

algorithms applied to dynamic flexible job shop scheduling problems. Inf Sci (Ny) 298:198–224. doi: 10.1016/j.ins.2014.11.036

239. Shrouf F, Ordieres-Meré J, García-Sánchez A, Ortega-Mier M (2014) Optimizing the production scheduling of a single machine to minimize total energy consumption costs. J Clean Prod 67:197–207. doi: 10.1016/j.jclepro.2013.12.024

240. Singh H, Gupta MM, Meitzler T, Hou Z, Garg KK, Solo AMG, Zadeh LA (2013) Real-Life Applications of Fuzzy Logic. 2013

241. Singh M, Srivastava RK (2018) Resources , Conservation & Recycling Analysis of external barriers to remanufacturing using grey-DEMATEL approach : An Indian perspective. Resour Conserv Recycl 136:79–87. doi: 10.1016/j.resconrec.2018.03.021

242. Srinoi P, Shayan E, Ghotb F (2006) A fuzzy logic modelling of dynamic scheduling in FMS. Int J Prod Res 44:1–21. doi: 10.1080/00207540500465493

243. Stadler C (2011) Process Innovation and Integration in Process-Oriented Settings: The Case of the Oil Industry. J Prod Innov Manag 28:44–62

244. Steinhauer D, Sikorra JN, Haux MA, Friedewald A, Lo H (2017) Processing incomplete data for simulation-based production planning in shipbuilding. J Simul. doi: 10.1057/s41273-016-0048-3

245. Su T, Lin Y (2014) problems for recoverable manufacturing systems. J Manuf Syst. doi: 10.1016/j.jmsy.2014.07.007

246. Su TS (2017) A fuzzy multi-objective linear programming model for solving remanufacturing planning problems with multiple products and joint components. Comput Ind Eng 110:242–254. doi: 10.1016/j.cie.2017.06.021

247. Subbaiah K V, Nageswara Rao M, Rao KN (2009) Scheduling of AGVs and machines in FMS with makespan criteria using sheep flock heredity algorithm. Int J Phys Sci 4:139–148

248. Sudiarso A, Labib AW (2002) A fuzzy logic approach to an integrated maintenance/production scheduling algorithm. Int J Prod Res 40:3121–3138. doi: 10.1080/00207540210146143

249. Talon A, Curt C (2017) Selection of appropriate defuzzification methods : application to the assessment of dam performance To cite this version : HAL Id : hal-01579184. doi: 10.1016/j.eswa.2016.09.004

250. Tan Y, Shen L, Langston C (2010) Construction project selection using fuzzy TOPSIS approach. J Model Manag 5:302–315. doi: 10.1108/17465661011092669

251. Tang D, Dai M, Salido MA, Giret A (2016) Energy-efficient dynamic scheduling for a flexible flow shop using an improved particle swarm optimization. Comput Ind 81:82–95. doi: 10.1016/j.compind.2015.10.001

252. Tavakkoli-Moghaddam R, Javadi B, Jolai F, Ghodratnama A (2010) The use of a fuzzy multi-objective linear programming for solving a multi-objective single-machine scheduling problem. Appl Soft Comput J 10:919–925. doi:

10.1016/j.asoc.2009.10.010

253. Taylan O, Bafail AO, Abdulaal RMS, Kabli MR (2014) Construction projects selection and risk assessment by fuzzy AHP and fuzzy TOPSIS methodologies. Appl Soft Comput J 17:105–116. doi: 10.1016/j.asoc.2014.01.003

254. Tedford JD, Lowe C (2003) Production scheduling using adaptable fuzzy logic with genetic algorithms. Int J Prod Res 41:2681–2697. doi: 10.1080/0020754031000090621

255. Thiagarajan S, Rajendran C (2005) Scheduling in dynamic assembly job-shops to minimize the sum of weighted earliness , weighted tardiness and weighted flowtime of jobs. Comput Ind Eng 49:463–503. doi: 10.1016/j.cie.2005.06.005

256. Tighe A, Smith FS, Lyons G (2005) Optimisation enhancement using self-organising fuzzy control. Kybernetes 34:1440–1455. doi: 10.1108/03684920510614759

257. Tiwary AP, Pradhan BB, Bhattacharyya B (2014) Application of multi-criteria decision making methods for selection of micro-EDM process parameters. Adv Manuf 2:251–258. doi: 10.1007/s40436-013-0050-1

258. Toksan MD, Ank OA (2017) Single machine scheduling problems under position-dependent fuzzy learning effect with fuzzy processing times. J Manuf Syst 45:159–179. doi: 10.1016/j.jmsy.2017.08.006

259. Trianni A, Cagno E, Thollander P, Backlund S (2013) Barriers to industrial energy efficiency in foundries: A European comparison. J Clean Prod 40:161–176. doi: 10.1016/j.jclepro.2012.08.040

260. Trillas E (2011) Lotfi A . Zadeh : On the man and his work. Sci Iran 18:574–579. doi: 10.1016/j.scient.2011.05.001

261. Tsai S, Zhou J, Gao Y, Wang J, Li G, Zheng Y, Ren P, Xu W (2017) Combining FMEA with DEMATEL models to solve production process problems. PLoS One 12:1–15

262. Tyagi S, Agrawal S, Yang K, Ying H (2017) An extended Fuzzy-AHP approach to rank the influences of socialization-externalization-combination-internalization modes on the development phase. Appl Soft Comput J 52:505–518. doi: 10.1016/j.asoc.2016.10.017

263. Uysal F, Tosun O (2012) Fuzzy TOPSIS-based computerized maintenance management system selection. J manfacturing Technol Manag 23:212–228. doi: 10.1108/17410381211202205

264. Vakhania N, Hernandez JA, Werner F (2014) Scheduling unrelated machines with two types of jobs. Int J Prod Res 52:3793–3801. doi: 10.1080/00207543.2014.888789

265. Vincent T (2011) Multicriteria models for just-in-time scheduling. Int J Prod Res 49:3191–3209. doi: 10.1080/00207541003733783

266. Vujanovic D, Momcilovic V, Bojovic N, Papic V, Vujanovic D (2012) Expert

Systems with Applications Evaluation of vehicle fleet maintenance management indicators by application of DEMATEL and ANP. Expert Syst Appl 39:10552–10563. doi: 10.1016/j.eswa.2012.02.159

267. Wang DJ, Liu F, Jin Y (2017) A multi-objective evolutionary algorithm guided by directed search for dynamic scheduling. Comput Oper Res 79:279–290. doi: 10.1016/j.cor.2016.04.024

268. Wang J, Qiao F, Zhao F, Sutherland JW (2016) Batch scheduling for minimal energy consumption and tardiness under uncertainties: A heat treatment application. CIRP Ann - Manuf Technol 65:17–20. doi: 10.1016/j.cirp.2016.04.115

269. Wang J, Zhang YF, Nee AYC, Wang YF, Fuh JYH (2009) Reducing tardy jobs by integrating process planning and scheduling functions. Int J Prod Res 47:6069–6084. doi: 10.1080/00207540802216388

270. Wang JJ, Liu YJ (2014) Single-machine bicriterion group scheduling with deteriorating setup times and job processing times. Appl Math Comput 242:309–314. doi: 10.1016/j.amc.2014.05.048

271. Wang K, Huang Y, Qin H (2015) A fuzzy logic-based hybrid estimation of distribution algorithm for distributed permutation fl owshop scheduling problems under machine breakdown. 1–15. doi: 10.1057/jors.2015.50

272. Wang L, Chu J, Wu J (2007) Selection of optimum maintenance strategies based on a fuzzy analytic hierarchy process. Int J Prod Econ 107:151–163. doi: 10.1016/j.ijpe.2006.08.005

273. Wang P, Zhu Z, Wang Y (2016) A novel hybrid MCDM model combining the SAW , TOPSIS and GRA methods based on experimental design. Inf Sci (Ny) 345:27–45. doi: 10.1016/j.ins.2016.01.076

274. Wang R, Zhou J, Yi X, Pantelous AA (2018) Solving the green - fuzzy vehicle routing problem using a revised hybrid intelligent algorithm. J Ambient Intell Humaniz Comput 0:0. doi: 10.1007/s12652-018-0703-9

275. Wang X, Huang W (2010) Fuzzy resource-constrained project scheduling problem for software development. Wuhan Univ J Nat Sci 15:25–30. doi: 10.1007/s11859-010-0106-z

276. Wang Y, He Z, Kerkhove LP, Vanhoucke M (2017) On the performance of priority rules for the stochastic resource constrained multi-project scheduling problem. Comput Ind Eng 114:223–234. doi: 10.1016/j.cie.2017.10.021

277. Wang YR, Chen AN (2016) Production Logistics Simulation and Optimization of Industrial Enterprise based on Flexsim. Int J Simul Model 15:732–741. doi: 10.2507/IJSIMM15(4)CO18

278. Wei Z, Liao W, Zhang L (2022) Hybrid energy-efficient scheduling measures for flexible job-shop problem with variable machining speeds. Expert Syst Appl 197:article 116785. doi: 10.1016/j.eswa.2022.116785

279. Wen H, Hou S, Liu Z, Liu Y (2017) An optimization algorithm for integrated remanufacturing production planning and scheduling system. Chaos, Solitons and

Fractals 105:69–76. doi: 10.1016/j.chaos.2017.10.012

280. Wen HJ, Smiths CH, Minors ED (1996) Formation and dynamic routeing of part families among flexible manufacturing cells. Int J Prod Res 34:2229–2245. doi: 10.1080/00207549608905022

281. Wong BK, Lai VS (2011) A survey of the application of fuzzy set theory in production and operations management: 1998-2009. Int J Prod Econ 129:157–168. doi: 10.1016/j.ijpe.2010.09.013

282. Wu H, Tsai Y (2011) A DEMATEL method to evaluate the causal relations among the criteria in auto spare parts industry. Appl Math Comput 218:2334–2342. doi: 10.1016/j.amc.2011.07.055

283. Wu HC (2010) Solving the fuzzy earliness and tardiness in scheduling problems by using genetic algorithms. Expert Syst Appl 37:4860–4866. doi: 10.1016/j.eswa.2009.12.029

284. Wu X, Guo P, Wang Y, Wang Y (2022) Decomposition approaches for parallel machine scheduling of step-deteriorating jobs to minimize total tardiness and energy consumption. Complex Intell Syst 8:1339–1354. doi: 10.1007/s40747-021-00601-9

285. Wu X, Sun Y (2018) A green scheduling algorithm for flexible job shop with energy-saving measures. J Clean Prod 172:3249–3264. doi: 10.1016/j.jclepro.2017.10.342

286. Xiao Y, Konak A (2017) A genetic algorithm with exact dynamic programming for the green vehicle routing & scheduling problem. J Clean Prod 167:1450–1463. doi: 10.1016/j.jclepro.2016.11.115

287. Yan J, Li L, Zhao F, Zhang F, Zhao Q (2016) A multi-level optimization approach for energy-efficient flexible flow shop scheduling. J Clean Prod 137:1543–1552. doi: 10.1016/j.jclepro.2016.06.161

288. Yao FS, Zhao M, Zhang H (2012) Two-stage hybrid flow shop scheduling with dynamic job arrivals. Comput Oper Res 39:1701–1712. doi: 10.1016/j.cor.2011.10.006

289. Yin Y, Cheng TCE, Wang D, Wu CC (2016) Improved Algorithms for Single-Machine Serial-Batch Scheduling with Rejection to Minimize Total Completion Time and Total Rejection Cost. IEEE Trans Syst Man, Cybern Syst 46:1578–1588. doi: 10.1109/TSMC.2015.2505644

290. Yong D (2006) Plant location selection based on fuzzy TOPSIS. Int J Adv Manuf Technol 28:839–844. doi: 10.1007/s00170-004-2436-5

291. Yu L, Shih HM, Sekiguchi T (1999) Fuzzy inference-based multiple criteria FMS scheduling. Int J Prod Res 37:2315–2333. doi: 10.1080/002075499190789

292. Yurdakul M, Tansel Y (2009) Analysis of the benefit generated by using fuzzy numbers in a TOPSIS model developed for machine tool selection problems. J Mater Process Technol 209:310–317. doi: 10.1016/j.jmatprotec.2008.02.006

293. Zadeh LA (1965) Fuzzy Sets. Inf Control 8:338–353

294. Zanakis SH, Solomon A, Wishart N, Dublish S (1998) Multi-attribute decision making : A simulation comparison of select methods. Eur J Oper Res 107:507–529

295. Zandieh M, Khatami AR, Rahmati SHA (2017) Flexible job shop scheduling under condition-based maintenance: Improved version of imperialist competitive algorithm. Appl Soft Comput 58:449–464. doi: 10.1016/j.asoc.2017.04.060

296. Zeppetella L, Gebennini E, Grassi A, Rimini B (2017) Optimal production scheduling with customer-driven demand substitution. Int J Prod Res 55:1692–1706. doi: 10.1080/00207543.2016.1223895

297. Zhai Y, Biel K, Zhao F, Sutherland JW (2017) Dynamic scheduling of a flow shop with on-site wind generation for energy cost reduction under real time electricity pricing. CIRP Ann - Manuf Technol 66:41–44. doi: 10.1016/j.cirp.2017.04.099

298. Zhang L, Deng Q, Zhao Y, Fan Q, Liu X, Gong G (2022) Joint optimization of demand-side operational utility and manufacture-side energy consumption in a distributed parallel machine environment. Comput Ind Eng 164:article 107863. doi: 10.1016/j.cie.2021.107863

299. Zhang L, Sun X, Xue H (2019) Identifying critical risks in Sponge City PPP projects using DEMATEL method : A case study of China. J Clean Prod 226:949–958. doi: 10.1016/j.jclepro.2019.04.067

300. Zhang Q, Zhou J, Wang K, Pantelous AA (2018) An Effective Solution Approach to Fuzzy Programming with Application to Project Scheduling. Int J Fuzzy Syst. doi: 10.1007/s40815-018-0542-z

301. Zhao C, Tang H (2010) Rescheduling problems with deteriorating jobs under disruptions. Appl Math Model 34:238–243. doi: 10.1016/j.apm.2009.03.037

302. Zhao H, Guo S (2014) Selecting Green Supplier of Thermal Power Equipment by Using a Hybrid MCDM Method for Sustainability. Sustainability 6:217–235. doi: 10.3390/su6010217

303. Zhou Q, Li G, Li J, Shu LC, Zhang C, Yang F (2017) Dynamic priority scheduling of periodic queries in on-demand data dissemination systems. Inf Syst 67:58–70. doi: 10.1016/j.is.2017.03.005

304. Zou X, Liu L, Li K, Li W (2018) A coordinated algorithm for integrated production scheduling and vehicle routing problem. Int J Prod Res 56:5005–5024. doi: 10.1080/00207543.2017.1378955

305. Zuo Y, Gu H, Xi Y (2008) Study on constraint scheduling algorithm for job shop problems with multiple constraint machines. Int J Prod Res 46:4785–4801. doi: 10.1080/00207540701324143

# Research paper publications

## A. Research Papers Published/accepted in Journals

1. **Sumit Chawla**, Ranganath M. Singari (2021), "Integrated TOPSIS-PROMETHEE-MOORA model for material selection of crankcase cover", Indian journal of engineering and material sciences (IJEMS), Vol. 28 (5), 454-461. **(SCI, Impact factor 0.881)**

2. **Sumit Chawla**, Ranganath M. Singari (2022), "Prioritizing scheduling parameters in the automotive industry using fuzzy TOPSIS-DEMATEL model", Journal of engineering research (JER), Special issue, 198-207. **(SCIE, Impact factor 0.64)**

3. **Sumit Chawla**, Ranganath M. Singari (2022), "Dispatching rule-based single machine static scheduling of crankcase covers", Advances in Transdisciplinary Engineering (ATDE). (**Scopus Indexed**, **Accepted)**

## B. Research Papers Presented/ Published in International / National Conference Proceedings

1. **Sumit Chawla**, Ranganath M. Singari, "Priority Sequencing Rule based Machine Shop Scheduling Problems", 3rd International Conference on Advanced Production and Industrial Engineering (ICAPIE'18) Organised by Centre for Advanced Production and Industrial Engineering Research (CAPIER), DTU, Delhi during October 5-6, 2018.

2. **Sumit Chawla**, Saurabh Agarwal, Ranganath M. Singari, "Integrated TOPSIS-MOORA Model for prioritization of new bike selection", 1st International Conference on Future Learning Aspects of Mechanical Engineering (FLAME- 2018), AMITY UNIVERSITY Noida during 3rd -5th Oct, 2018.

3. **Sumit Chawla**, Ranganath M. Singari, "Route Selection of Jobs in FMS using Fuzzy Set Approach, 2nd International Conference on Advanced Production and Industrial Engineering, DTU (formerly DCE) during Oct 6-7, 2017.

4. Reetik Kaushik, Nikita Deswal, Anurag Dudpuri, **Sumit Chawla**, Ranganath M. Singari, "Study of Grey Fuzzy Optimization Techniques for FMS Scheduling Problem", 4th International Conference on Advanced Production and Industrial Engineering (ICAPIE'19) Organised by Centre for Advanced Production and Industrial Engineering Research (CAPIER), DTU, Delhi during October 4-5, 2019.

## C. Research Papers Communicated in Journals

1. **Sumit Chawla**, Ranganath M. Singari, "Modelling and simulation of crankcase cover manufacturing in the automobile industry", Journal of scientific and industrial research. **(SCIE, Impact factor 1.056)**

2. **Sumit Chawla**, Ranganath M. Singari, "Integrated fuzzy AHP-TOPSIS model for material selection of motorcycle chain", soft computing. **(SCIE, Impact factor 3.643)**

# Curriculum Vitae

**Sumit Chawla**

chawlasumit4@gmail.com
Mob. +91 9910749657

## Personal Details:

Date of Birth: 16th Feb 1991

Address: Wz-1409 A Nangal Raya New Delhi 110046

## Educational Qualifications:

- **M.Tech**
  University: MNIT Jaipur, Rajasthan, India; Manufacturing System Engineering; 2014.

- **B.Tech**
  University: Guru Gobind Singh Indraprastha University, Delhi, India; Mechanical & Automation, 2012.

**Awards:** Gold Medallist in M.Tech.

**Experience:** Total Experience- **8 Years**

- Working as an Assistant Professor in "**Bharati Vidyapeeth's College of Engineering**" affiliated to **GGSIP University** from 1st Aug 2017 to till now.
- Worked as an Assistant Professor in "**Delhi Technical Campus**" affiliated to **GGSIP University** from 4th Aug 2014 to 20th July 2017.

**Number of Research Publications:** 06 Published; 01 Accepted; 02 Communicated

## International / National Workshops / Short-term-courses

- Participated in AICTE recognized short term course on "**Scilab Programming**" through ICT conducted by **NITTTR Chandigarh** from 14th May to 18th May 2018 at Bharati Vidyapeeth's college of Engineering, New Delhi.
- Attended the one-week online FDP on "**Recent trends in Material science and engineering**" organized by the Sharda University, Greater noida, Uttar Pradesh during May 25-31,2020.
- Participated in 4 Days of online FDP Program on "**ICT/LMS Tools for Teaching & Learning**" organized by Department of Information Technology & IQAC of K.C. College of Engineering & Management Studies & Research, Thane (E) from 16- 19 June 2020.
- Participated in TEQIP-III sponsored one-week STTP on "**Multiple Attribute Decision Making and Its Industrial Applications**" organized by the **S. V. National Institute of Technology Surat**, from March 15-19, 2021.
- Participated in two-week online FDP on "**Scientific Computations and GUI Development using MATLAB**" organized by the **PDPM IIITDM Jabalpur** during March 21-31, 2022.