Int j simul model 19 (2020) 1, 65-76
ISSN 1726-4529 Original scientific paper

# SIMULATION STUDY OF A FLEXIBLE MANUFACTURING SYSTEM REGARDING SUSTAINABILITY

Ojstersek, R.; Acko, B. & Buchmeister, B.
University of Maribor, Faculty of Mechanical Engineering, Smetanova 17, 2000 Maribor, Slovenia
E-Mail: robert.ojstersek@um.si, bojan.acko@um.si, borut.buchmeister@um.si

**Abstract**
The presented manuscript deals with the impact of manufacturing flexibility on the sustainability justification of the manufacturing system, related to manufacturing sustainable social, environmental and financial impact. Such impact is not described in the research sphere. The complexity of the optimisation parameters is reflected in the multi-objective nature that can be evaluated with the use of the simulation study method. The manuscript presents a description of manufacturing flexibility modelling, with respect to the four-level architectural model, describing an optimisation problem of high-mix low-volume production. The impact of manufacturing flexibility on the sustainability justification is presented by the new block diagram. Sustainability parameters' mathematical modelling is presented with two main optimisation parameters of energy consumption and machine scrap percentage. The impact is evaluated and described by an appropriate multi-criteria optimisation method on a sustainably justified production system.
(Received in September 2019, accepted in March 2020. This paper was with the authors 1 month for 1 revision.)

**Key Words:** Manufacturing Flexibility, Sustainable Manufacturing, Simulation Modelling, Simio, Flexible Job Shop Scheduling Problem, Evolutionary Computation

## 1. INTRODUCTION

Worldwide manufacturing trend is based on providing personalised products to customers. A high degree of personalisation is not only present in high-mix low-volume manufacturing systems, but is also seen in mass production systems [1]. The high degree of manufacturing flexibility to the demands and wishes of customers introduces in the manufacturing systems the component of flexibility, and the importance of its optimisation to the sustainable justification of manufacturing systems [2]. The impact of manufacturing flexibility on its sustainable viability has not yet been investigated thoroughly [3]. It is safe to say that in order to ensure sustainable production, this is an important optimisation parameter that must be well described and evaluated [4]. Individual research works address the field of manufacturing flexibility optimisation and its impact on sustainable eligibility separately. Optimisation problem of manufacturing scheduling custom production is defined mathematically as an NP-hard multi-objective optimisation problem, and, thus, is difficult to solve [5]. The authors present different optimisation approaches that use different methods of evolutionary computation to determine the optimal optimisation objective related to flow times, machine utilisation, costs, etc. [6]. In the literature, we could not find a comprehensive optimisation approach that would present, evaluate, and solve the optimisation problem of the manufacturing flexibility impact on its sustainable justification by a comprehensive optimisation approach [7]. The limitations relate to the complexity of mathematical modelling of manufacturing flexibility, and associated data that evaluate the manufacturing sustainability adequately. Manufacturing flexibility can be structured fundamentally, using a four-level architectural model that allows comprehensive consideration of optimisation parameters, ranging from transportation, production capacity, product type and characteristics, and order series diversity [8]. With certainty, it can be argued that, when it comes to manufacturing orders' scheduling, its impact on the sustainable justification of manufacturing electric energy consumption, materials use, natural resources, social aspects of employees and the company, and, the most important financial, the viability of the manufacturing system, is important [9]. In the research work, we present a new method of simulation study approach, which addresses the problem of high-mix low-volume manufacturing scheduling comprehensively, in which a high degree of flexibility is essential to evaluate its sustainable viability. Mathematical modelling of manufacturing flexibility and parameters affecting sustainable viability are presented, based on a four-level architectural model. A simulation study conducted in the Simio simulation environment and the self-developed IHKA evolutionary computation method, allow optimal allocation of work orders from the standpoint of sustainable manufacturing justification [10, 11]. The proposed mathematical and simulation modelling method is evaluated with two benchmark datasets [12, 13], and one dataset from a real-world manufacturing system, on the basis of which a comparison is made between optimised and non-optimised manufacturing systems. The simulation study examines the simulation model according to the newly proposed block structure, which enables a holistic optimisation approach, and, thus, the evaluation of the production system's environmental, social and financial viability. The influence of parameters such as electricity consumption and the scrap rate in relation to the age of the machines, allow a comprehensive consideration of the presented research question.

## 2. PROBLEM DESCRIPTION

The importance of the manufacturing flexibility impact does not relate exclusively to smaller production of a company with a specific job shop or flexible job shop production type [14, 15], but we can trace the trend of manufacturing flexibility phenomena in other types of production. The impact of personalisation requires some flexibility for each production type, including mass production type. The manuscript presents two key research questions related to manufacturing flexibility production modelling and it’s relation to the sustainable orientation and justified manufacturing system. The full definition of manufacturing flexibility and its effects on sustainable eligibility are unknown. Using the proposed four-level architectural model, we define the flexibility of production as a comprehensive multi-objective optimisation problem. The integrity of the presented architectural model makes it possible to determine the importance of simulation modelling methods to define and optimise flexible manufacturing systems' sustainability. A comprehensive optimisation approach enables detailed evaluation and optimisation of the manufacturing system with respect to the three key parameters of manufacturing flexibility with respect to the cost-time diagram, depending on manufacturing flexibility [9]. It was found that, in addition to the above characteristics, a flexible manufacturing system can also be evaluated for cost, time, and environmental sustainability.

### 2.1 Manufacturing flexibility

The impact of manufacturing flexibility in smaller manufacturing systems and high mass production personalisation define manufacturing flexibility as an NP-hard optimisation problem. Manufacturing flexibility can be defined either as in an adaptive or proactive manner. Defensive/reactive use in the adaptive approach represents the flexibility to accommodate unknown uncertainties in a manufacturing system. In this case, accommodated uncertainties address both the internal, as well as external uncertainties faced by manufacturing companies. An adaptive approach can define manufacturing flexibility as a manufacturer's ability to adapt to different requirements and changes in the global market. A proactive approach describes how the use of flexibility aids the company in gaining global competitiveness by raising customer anticipation (customer new products' design) and increasing the insecurity of enterprise rivals (globalisation of manufacturing systems). With a proactive approach, we can define manufacturing flexibility as a system's ability to adapt to a wide range of possible dynamical environmental changes. From a sustainable manufacturing viewpoint, manufacturing flexibility should be customer-driven, and refers to the new product design in relation to the personalised products that meet customer needs. Literature explains that it is the ability of a manufacturing system to respond to cost, time, and technological demands effectively within a short period to changing product needs and requirements [8]. Manufacturing efficiency describes that all system resources must be planned and scheduled optimally using advanced evolutionary computation methods. Manufacturing flexibility can be described by the four-level architecture, as presented in Table I. Effectively optimising the manufacturing system from the standpoint of manufacturing flexibility requires addressing the optimisation problem at all four architectural levels. The relevant multi-objective optimisation method must address the conflicting optimisation parameters adequately. The optimisation approach takes into account all the optimisation functional dependencies shown in Table I.

Table I: Manufacturing flexibility four-level architecture model classification.

| Level | Description |
|---|---|
| Individual resource level | Individual resource level refers to flexibility associated with a resource.<br>Labour flexibility, machine flexibility and material handling flexibility are included. |
| Shop floor level | Shop floor level refers to flexibility associated with the shop floor.<br>Routing flexibility and operation flexibility are included. |
| Plant level | Plant level refers to flexibility associated with plant.<br>Volume flexibility, mix flexibility, expansion flexibility and product flexibility, modification flexibility and new product flexibility are included. |
| Functional level | Functional level describes manufacturing flexibility. |

The complexity of manufacturing flexibility optimisation can be described as market demand uncertainty referring to the occurrence of an unexpected change (within the manufacturing system or market dynamic changes). Dynamic variability of new products and new products' design within the manufacturing process refers to the flexibility of an advanced personalised high-mix variety of products. New products' design and dynamic variability of manufactured products can be divided in two different ways: the range of parts produced in the existing manufacturing system within a high-mix production type, or, the variation of products' output over time, described as a low-volume production type. These two types defined high-mix low-volume production type, within which we can distinguish between two types of changes: planned and unplanned changes. In sustainable oriented manufacturing systems, planned changes can be optimised accordingly without any cost, time and environmental inefficiency of the manufacturing system. Unplanned changes must be eliminated to the maximum possible degree, due to their characteristic that they occur independently, with unplanned response times. Manufacturing flexibility definition by the planned and unplanned changes leads to six flexibility dimensions: machine, operation, routing, volume, expansion, product and process flexibility. The presented research work refers mostly to manufacturing process flexibility and its manufacturing sustainability, described as: the ability to produce a given set of part types, each possibly using a different material, in several different sets of part types that the system can produce without major set-ups [16], number and variety of products which can be produced without incurring high transition penalties or large changes in performance outcomes.

## 2.2 Sustainable manufacturing

Sustainability and sustainable manufacturing is, in the time of Industry 4.0, a wide research field, due the urgency of reducing environmental loads of industrial production. Sustainable manufacturing issues are investigated widely in the manufacturing types of high-mix, low-volume to mass production. It involves developing long lasting products with comprehensive life-cycle considerations, and implementing sustainable manufacturing processes and systems that are able to minimise negative environmental impacts, minimise consumption of natural materials, energy consumption, and other resources. All involved stockholders must be economically sound and societally beneficial. Sustainability is the driver for innovation and creative thinking. Innovation and encouragement creativity thinking promotes accelerated growth in manufacturing and new products' design. Societal well-being and economic growth, with appropriate cost-time investment [2], depend heavily on the level and quality of optimised manufacturing systems.

Optimised manufacturing processes must minimise negative environmental impacts. Manufacturing systems' multi-objective optimisation parameters must concern conserving energy (machine operation and idle energy consumption) and natural resources (natural material waste management), remanufacture and scrap improvement around assembly, related to repairability and disassembly. The main aim of sustainable manufacturing is to introduce a new holistic presence product cycle, and optimise the lifecycle of manufacturing systems, products and services. Sustainable manufacturing's five main fields are: system optimisation on three main objectives (minimises energy consumption, material and products' waste, optimises manufacturing processes and techniques related to manufacturing methods, production utilisation, manufacturing flexibility, lower production and labour costs, and high systems' efficiency); increased energy efficiency of operation and idle times; lower, cleaner and renewable energy use with the optimisation aspect of transport and material handling; manufacturing processes with minor pollution, lower waste disposal and emission production; industrial symbioses using new optimisation techniques for sustainable natural cycles in manufacturing systems, related to mathematical and simulation modelling techniques using simulation scenarios to ensure sustainable manufacturing systems.

## 3. SIMULATION STUDY

The simulation study was conducted using the well-known research optimisation problem of FJSSP. The Kacem 10×10 datasets and the Brandimarte Mk08 benchmark dataset were selected as the basis for the simulation modelling study. The presented simulation study also used the RW_PS data set, which describes a real-world manufacturing system input data, to confirm the new simulation study approach efficiency. Multi-objective FJSSP optimisation problem generally refers to the optimisation of three main parameters: flow time, average machine utilisation and elimination of possible bottlenecks in the manufacturing system. In order to optimise the FJSSP system from the manufacturing flexibility point of view and the sustainable eligibility, the FJSSP optimisation problem needs to be described further mathematically, and the optimisation parameters should be defined with respect to the impact of manufacturing flexibility (high-mix, low-volume) and sustainable eligibility. The following section presents a comprehensive introduction to a simulation modelling approach, which studies the impact of manufacturing flexibility from the point of view of machine size, cost, layout, transport, time, etc.

### 3.1 Manufacturing flexibility modelling

The definition of manufacturing flexibility in Table I describes FJSSP as a manufacturing system in which flexibility is present on the shop floor level. Determining the impact of the individual parameters from all four levels of the architectural model must be described thoroughly mathematically and data-based. Most commonly, benchmark data sets are used, to which some additional data must be added related to costs, product mix, product volume, machine-workplaces dimensions and setup times. The presented additional data were generated mathematically with appropriate interdependence functions. In the use of a real-world data set, some constant values from the manufacturing system were used to ensure the comprehensiveness of the simulation results. The machine classification into three groups according to their characteristics enables detailed optimisation with respect to key optimisation parameters related to the manufacturing flexibility and sustainable justification of the manufacturing system. The method of mathematical modelling determines the interdependencies between machine groups and optimisation parameters. It is based on the method of functional dependencies' discrete modelling [17]. Table II shows three machine groups, divided by the operating and idle costs of the machines, calculated by the discrete model factor. The correlation factor between operational and idle cost classifies machines as group $G_1$, represented by small machines, group $G_2$, medium machines, and group $G_3$, large machines. According to the machine classification, operational cost range is between 30 to 60 EUR/h. Manufacturing system individual machine classification can be made according to the proposed approach of discrete factor calculation. Values presented in Table II are made according to the fixed costs of individual groups and the recalculated idle cost of the machines. The recommendations in [18] have defined fixed costs as 40 % in a case of a small machine, 50 % in a case of a medium-sized machine, and 60 % of a fixed cost in a case of a large machine. The manufacturing company's production capabilities can be divided into three groups, according to which, the optimisation of the flexibility and sustainable justification of manufacturing system can be carried out. The number of groups, range and interdependencies can be adjusted according to the specific optimisation problem.

Table II: Machine group costs' classification.

| **Group** | **Operational cost** (EUR/h) | **Fixed cost** (%) | **Idle cost** (EUR/h) | **Factor** |
|---|---|---|---|---|
| $G_1$ | 30 – 40 | 40 | 12 – 16 | $x$ = 2/5 |
| $G_2$ | 41 – 50 | 50 | 20.5 – 25 | $x$ = 1/2 |
| $G_3$ | 51 – 60 | 60 | 30.6 – 36 | $x$ = 3/5 |

In defining the performance and characteristics of individual machines, it is necessary to link the interdependence of individual parameters adequately, especially when adding parameters through mathematical modelling of randomly distributed values. The group size determination depends on the operating and idle costs' calculation. The idle cost values were modelled mathematically using the method of discrete values' determination according to the correlation factor shown in Table II. The cost value of operation and idle are defined in Table III by the setup time of operations, which allows determining the cost-time function of the manufacturing system. The constant values of the machines' layout position in the production system are determined according to the two-axis coordinate $x$, $y$ system.

Table III: Dataset evaluation parameters.

| **Machine** | $M_1$ | $M_2$ | $M_3$ | $M_4$ | $M_5$ | $M_6$ | $M_7$ | $M_8$ | $M_9$ | $M_{10}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Group classification | $G_2$ | $G_1$ | $G_1$ | $G_3$ | $G_3$ | $G_3$ | $G_1$ | $G_2$ | $G_1$ | $G_2$ |
| Operational cost (EUR/h) | 43 | 35 | 39 | 53 | 52 | 59 | 36 | 45 | 38 | 45 |
| Idle cost (EUR/h) | 21.5 | 14 | 15.6 | 31.8 | 31.2 | 35.4 | 14.4 | 22.5 | 15.2 | 22.5 |
| $x_{loc}$ (m) | 0 | 0 | 5 | 5 | 10 | 10 | 15 | 15 | 20 | 20 |
| $y_{loc}$ (m) | 0 | 5 | 0 | 5 | 0 | 5 | 0 | 5 | 0 | 5 |
| Setup time (min) | 16 | 15 | 50 | 24 | 35 | 38 | 16 | 22 | 18 | 39 |

Values presented in Table IV describe individual variables according to the three group classification. The data show the values used in the simulation study and the basis on which the IHKA method [10] optimised the manufacturing system. The parameters were determined of cost, energy consumption, state of the production facility and other related data. For the calculation of data in Table IV, some assumptions must be made, such as: the production system operates in two shifts; financing the purchase of machinery (50 % own funds, 50 %

loan with 8 % interest); electricity value constant 8 EUR / 100 kWh; 4 % maintenance cost; annual facility costs 100 EUR / m$^2$ and 4 % additional operating costs.

Table IV: Individual variables mathematical values' classification.

| Data | $G_1$ | $G_2$ | $G_3$ |
|---|---|---|---|
| Purchase price of the machine (EUR) | 20,000 | 70,000 | 200,000 |
| Machine power (kW) | 4 | 10 | 25 |
| Workplace surface (m$^2$) | 10 | 20 | 30 |
| Depreciation period (year) | 8 | 8 | 8 |
| Useful capacity of the machine (h/year) | 3,000 | 3,200 | 3,400 |
| Energy costs (EUR/kWh) | 0.40 | 1.00 | 2.50 |
| Tool costs (EUR/h) | 2 | 3 | 4 |
| Costs of machine (EUR/h) | 3.95 | 8.67 | 18.27 |
| Worker gross costs (EUR/h) | 8 | 10 | 12 |
| Additional costs (EUR/h) | 0.16 | 0.35 | 0.73 |
| Workplace costs (EUR/h) | 12.11 | 19.02 | 31.00 |
| Variable costs (%) | 12.8 | 24.6 | 38 |

### 3.2 Manufacturing sustainability modelling

The sustainable viability of a manufacturing system is the key to effective cost-time investment. Simulation modelling of sustainable eligibility involves a comprehensive treatment of the manufacturing system, the product, and all participants in the creation of the product. The presented research work focuses on the evaluation of the manufacturing flexibility impact on the manufacturing system, and the importance of appropriate optimisation with regard to the sustainability of the company. Fig. 1 represents the basic characteristics of a sustainable manufacturing system. The key to optimising sustainable viability is a holistic view of the existing optimised system. In the initial phase, sustainably justified production deals with the design of the product or order that the production will produce, the technological process, the consumption of energy, natural materials, the provision of high quality, and in the feedback with the product, which guarantees a long life-cycle with the ability to introduce constant process improvements. It can be seen that an optimised planned and scheduled manufacturing system is crucial, which, with its high efficiency, enables a sustainable justified production from the point of view of energy consumption, reduction of waste production, natural material and scrap optimisation, high quality of products and broader company's social responsibility.

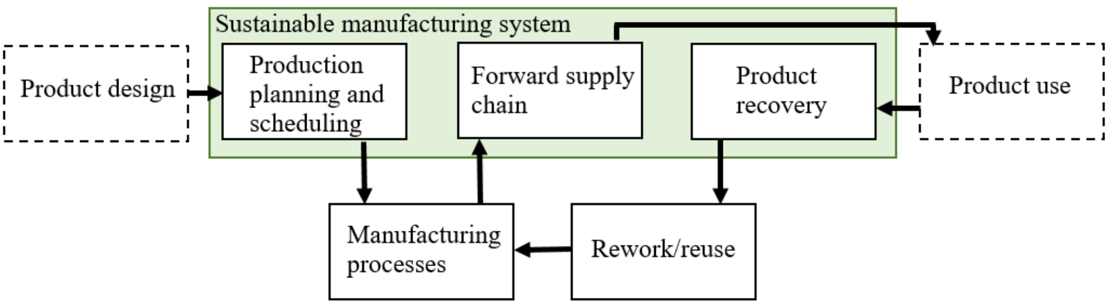


Figure 1: Manufacturing sustainability modelling block diagram.

Our work is based on determining the correlation between the percentage of machines' scrap in terms of age, and the amount of downtime of individual machines. The second optimisation parameter of manufacturing sustainability relates to the determination of energy consumption during operation and idle for the machine to perform the operation. The optimisation of these parameters was performed using the IHKA evolutionary computation method, which allocates work orders and individual operations optimally, according to the available machines and their parameters, while trying to satisfy the specified parameters. The optimal allocation of work orders affects the manufacturing system significantly, which is closely dependent on the manufacturing flexibility.

Modelling of single machine scrap percentages was performed using the classification of machines into three groups according to their age ($Sg_1$, $Sg_2$ and $Sg_3$). Table IV shows that the mathematical model predicts a machine depreciation period of 8 years. With this depreciation period, the linear function and a three-level classification, the individual values of the scrap percentages used by the optimisation algorithm in the optimal determination of work operations can be determined with respect to the available machines. Fig. 2 shows a graph of the functional relationship between the scrap percentage and the age of the machine. With the proposed method, we can define machine scrap values individually. The advantage of the presented method is the possibility of using a data-driven simulation model, which can assign a specific (realistic) functional dependence between the percentage of waste and the age of the machine.

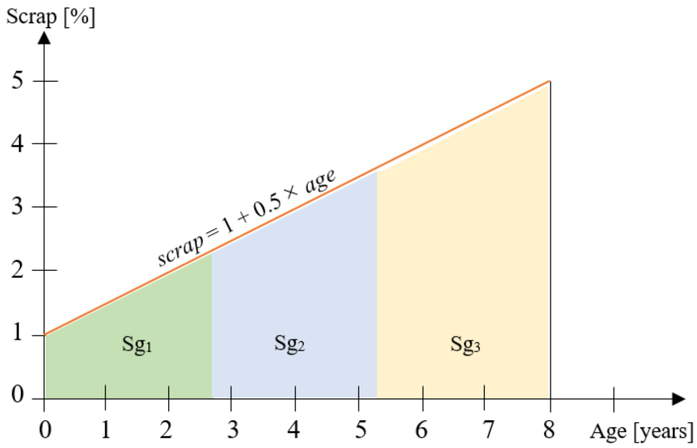

Figure 2: Scrap percentage modelling diagram.

Following the pattern of using the values from Table IV to determine the scrap percentages, the values of the energy consumed by each machine were determined by the values of electricity consumption at the operation and idle times. The constant value of the factor between electricity consumption during operation and standby time was 0.15, which was used according to the literature [18].

Table V: Scrap percentage machines' classification.

| **Machine** | $M_1$ | $M_2$ | $M_3$ | $M_4$ | $M_5$ | $M_6$ | $M_7$ | $M_8$ | $M_9$ | $M_{10}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Group classification | $G_2$ | $G_1$ | $G_1$ | $G_3$ | $G_3$ | $G_3$ | $G_1$ | $G_2$ | $G_1$ | $G_2$ |
| Machine operation energy consumption (kWh) | 10 | 4 | 4 | 25 | 25 | 25 | 4 | 10 | 4 | 10 |
| Machine idle energy consumption (kWh) | 1.5 | 0.6 | 0.6 | 3.75 | 3.75 | 3.75 | 0.6 | 1.5 | 0.6 | 1.5 |
| Machine age (years) | 2 | 1 | 6 | 7 | 8 | 1 | 2 | 5 | 6 | 1 |
| Machine scrap (%) | 2 | 1.5 | 4 | 4.5 | 5 | 1.5 | 2 | 3.5 | 4 | 1.5 |

Table V presents the modelled data that can be used to analyse the impact of manufacturing flexibility on sustainable viability. In the initial phase, the machines are divided into three basic classification types, followed by the allocation of the value of electricity consumption at the operation time, and by calculation of the mathematically determined values of energy idle consumption. Single machine scrap percentage is also determined mathematically with respect to the linear functional relationship between age and the associated scrap rate.

### 3.3 Simulation study of a real-world manufacturing system

The ability to evaluate the impact of manufacturing flexibility on the manufacturing system's sustainable eligibility cannot be determined only with the use of the benchmark datasets (Kacem and Brandimarte datasets); the appropriate simulation method must be evaluated using the data from a real-world manufacturing system. The following is a realistic manufacturing system of a smaller company in the European Union that manufactures custom products in smaller batches, and represents a typical high-mix low-volume type of production. Manufacturing system data were captured directly in the manufacturing company, and any missing data were collected from different manufacturing documentation to ensure a data driven discrete simulation modelling approach. A simulation model was built in the Simio software environment; 3-D model is represented by Fig. 3. The modelled manufacturing system consists of twelve machines, which, according to the classification presented above, are divided into three groups according to their size. Machine centres represent operations of cutting, manual welding, robotic welding, machining, assembly and operation of final control.

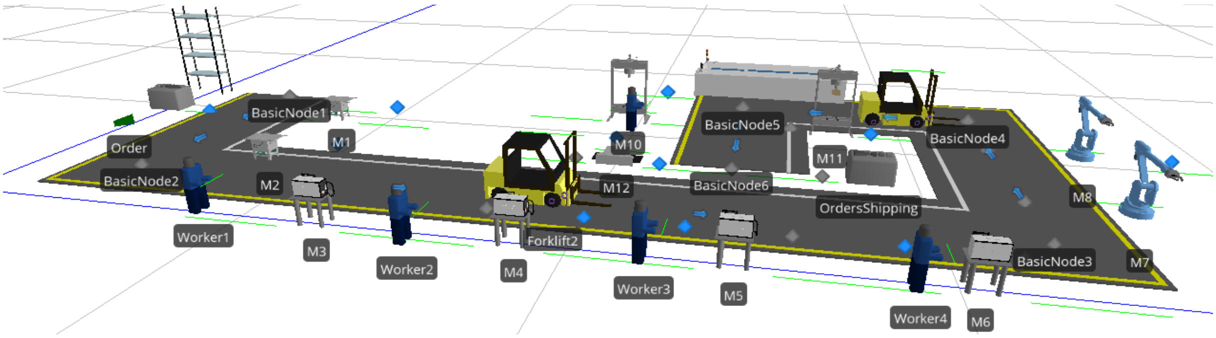


Figure 3: Simio simulation model.

Table VI: Real-world manufacturing systems dataset parameters.

| Machine | $M_1$ | $M_2$ | $M_3$ | $M_4$ | $M_5$ | $M_6$ | $M_7$ | $M_8$ | $M_9$ | $M_{10}$ | $M_{11}$ | $M_{12}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Group classification | $G_2$ | $G_2$ | $G_1$ | $G_1$ | $G_1$ | $G_1$ | $G_3$ | $G_3$ | $G_3$ | $G_2$ | $G_2$ | $G_1$ |
| Process time (min) | 20 | 24 | 40 | 45 | 38 | 47 | 20 | 25 | 11 | 22 | 20 | 12 |
| Usage cost (EUR) | 45 | 45 | 35 | 35 | 35 | 35 | 52 | 52 | 59 | 43 | 43 | 35 |
| Idle cost (EUR) | 22.5 | 22.5 | 14 | 14 | 14 | 14 | 31.2 | 31.2 | 35.4 | 21.5 | 21.5 | 15 |
| $x_{loc}$ (m) | 8 | 8 | 12.5 | 18.5 | 24.5 | 30.5 | 36 | 36 | 24.5 | 19.5 | 27.5 | 20 |
| $y_{loc}$ (m) | 9.5 | 4.5 | 0 | 0 | 0 | 0 | 5.5 | 10.5 | 16.5 | 12 | 12 | 7 |
| Setup time (min) | 10 | 10 | 15 | 15 | 15 | 15 | 8 | 8 | 18 | 7 | 7 | 3 |
| Machine operation energy consumption (kWh) | 10 | 10 | 4 | 4 | 4 | 4 | 25 | 25 | 25 | 10 | 10 | 4 |
| Machine idle energy consumption (kWh) | 1.5 | 1.5 | 0.6 | 0.6 | 0.6 | 0.6 | 3.75 | 3.75 | 3.75 | 1.5 | 1.5 | 0.6 |
| Machine age (years) | 2 | 1 | 6 | 7 | 8 | 1 | 2 | 5 | 6 | 1 | 4 | 2 |
| Machine scrap (%) | 2 | 1.5 | 4 | 4.5 | 5 | 1.5 | 2 | 3.5 | 4 | 1.5 | 3 | 2 |

Table VI shows the input data of the data-driven simulation model. The data cover process times, financial evaluation of process, processing times and idle times, and real machine positions in the manufacturing facilities are assigned to the $x$ and $y$ coordinate system. Depending on the technology sheet of individual orders, machine set times are calculated mathematically. The machine data sheets determine the electrical energy consumption of machines in operating and idle modes. The intended scrap percentage rate was determined by the scrap percentage of individual machines and real age of the machine. Based on the data described, a simulation study was conducted on the impact of manufacturing flexibility on sustainable viability, and the importance of adequate scheduling optimisation of the manufacturing system.

## 4. RESULTS AND DISCUSSION

The simulation study was conducted with two separate optimisation methods. The first part was a simulation study of an optimised production system, performed using the IHKA evolutionary computation optimisation algorithm. The second part of the simulation study was the application of conventional optimisation priority rules to determine the optimal production schedule. After two separate optimisation methods, the simulation results show that the optimisation results were significantly different, so the optimisation results obtained by the IHKA evolutionary computation method were called the optimised system, and the results of the conventional technique optimisation were called a non-optimised system. The simulation study evaluated the impact of manufacturing flexibility on sustainable eligibility using three datasets: Kacem 10×10, Brandimarte Mk08, and the real-world manufacturing system RW_PS dataset. The obtained simulation results support the choice of using three substantially different benchmark datasets. For the Kacem 10×10 dataset, the optimisation algorithm-method for determining the sequence of single operation execution is available to all machines from the set of machines, each operation can be performed on any available machine (theoretical dataset, intended primarily for evaluating the performance of the optimisation approach). However, for the other two datasets (Mk08 and RW_PS), the individual operation must be performed on a machine that is suitable for that operation, e.g. the welding operation can only be performed at the welding workplace (a real dataset intended to evaluate the applicability of the optimisation approach).

Table VII shows the results of the manufacturing system's optimisation by the parameter of electricity energy consumption at the time of order execution.

Table VII: Machine electrical energy consumption.

| | **Optimised** | | | **Non-optimised** | | |
|---|---|---|---|---|---|---|
| **Dataset** | Machine operation energy consumption (kWh) | Machine idle energy consumption (kWh) | ∑ (kWh) | Machine operation energy consumption (kWh) | Machine idle energy consumption (kWh) | ∑ (kWh) |
| Kacem 10×10 | 1008 | 66.6 | 1074.6 | 1154 | 135.45 | 1289.45 |
| Mk08 | 5167 | 876.6 | 6043.6 | 5167 | 1289.55 | 6456.55 |
| RW_PS | 344.2 | 66.81 | 411 | 344.2 | 87.88 | 432.1 |

The numerical results demonstrate the importance of using advanced evolutionary computing methods to determine the optimal allocation of work orders with respect to energy consumed during operations and minimise idle time, resulting in the sustainable consumption of natural raw materials and energy efficiency. With the Kacem 10×10 dataset, we see the importance of optimising order schedules based on the allocation of individual operations to a specific machine. The results of an optimised manufacturing system ensure a 20 % reduction in electricity consumption for the same set of orders. In this case, the energy consumption during processing was 14.5 % higher in relation to the non-optimised system, while significantly longer waiting times also led to 103.4 % less electrical energy consumption while waiting with the optimised manufacturing system. The Mk08 and RW_PS datasets confirm the validity of the simulation model for both optimisation approaches, since the power consumption at the processing time is identical for both systems. The same electrical consumption at the time of processing is attributed to the input data structure of the Mk08 and RW_PS datasets, subject to the condition that a particular operation must be performed only at a specific machine, which is determined in the order manufacturing data. Determining the electrical energy consumption while waiting for the operation to complete depends on the ability to optimise the scheduling of the work task appropriately. The idle energy consumption results show that, in the Mk08 dataset, the total electricity energy consumption of the non-optimised manufacturing system increased by 6.8 % compared to the optimised manufacturing system. A similar increase in electricity consumption of 5.1 % in the non-optimised production system can be seen in the optimisation data of the real-world manufacturing system.

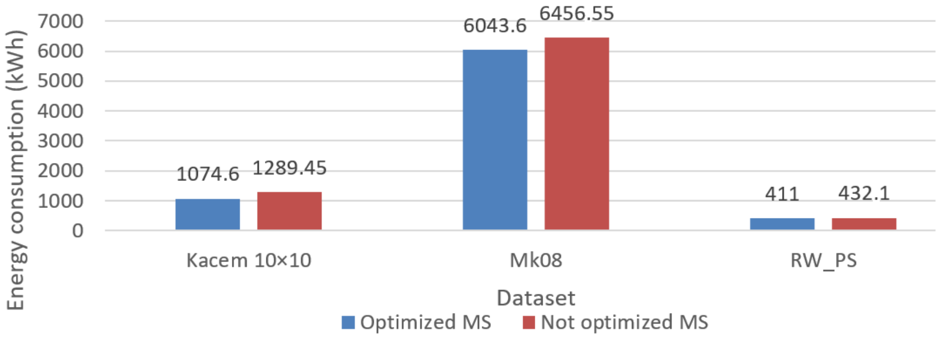


Figure 4: Optimised and non-optimised manufacturing system electrical energy consumption results.

The numerical optimisation results shown in Table VII are presented graphically in Fig. 4, where the optimisation results for the individual datasets represent the following economical calculations. Given the value of electricity, 8 EUR / 100 kWh and the operation of production in two shifts, the numerical calculation shows the savings between the optimised and non-optimised production systems, 1370.8 EUR for the Kacem 10×10 dataset, 5418 EUR for the Mk08 dataset, and 1087.1 EUR for the dataset RW_PS.

Machine age and scrap percentage modelling is represented by the numerical results in Table VIII and the graphical results in Fig. 5. The simulation displacement was performed by the method of simulation scenarios, where the reference simulation scenario RS assumes an average machine scrap rate of 3.45 % (machine placed in the $Sg_2$ group), simulation scenario S1, with the average age of the machines in the $Sg_1$ group, has an average scrap rate of 1.75 % and the machines placed in the $Sg_3$ group have an average scrap rate of 4.4 %.

Table VIII: Machines scrap percentages.

| | Scrap (%) | | |
|---|---|---|---|
| **Dataset** | RS | S1 | S2 |
| Kacem 10×10 | 2.74 | 2.23 | 3.47 |
| Mk08 | 3.22 | 2.75 | 3.33 |
| RW_PS | 2.70 | 2.10 | 3.20 |

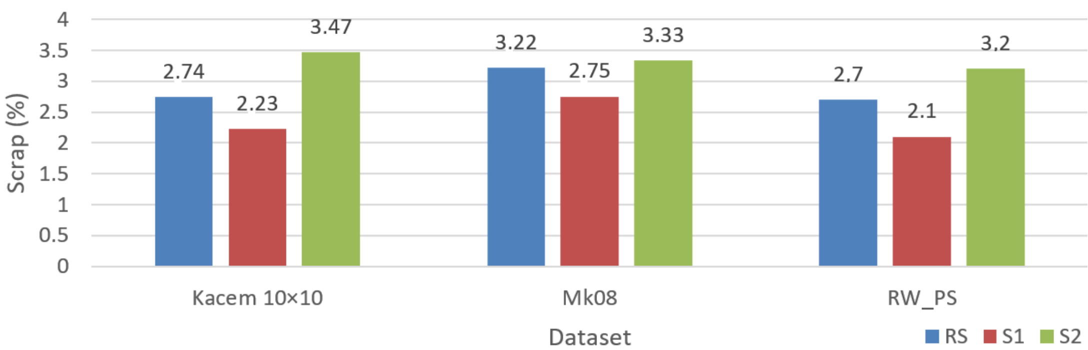


Figure 5: Simulation study scrap percentage modelling results.

The simulation results show that the scrap percentage depends significantly on the age of the machine. For the Kacem 10×10 dataset, the scrap rate for the optimal arrangement of machines in the $Sg_1$ group is 2.23 %, for machines in the $Sg_2$ group is 2.74 %, for non-optimally distributed work orders in $Sg_3$ is 3.47 %. The non-optimal allocation of work orders in this case represents a 55 % scrap increase in the output between the optimal scenario S1 and the non-optimal scenario S2. The Mk08 dataset shows the importance of proper production optimisation from the scrap rate point of view. The difference between the simulation scenarios S1 and S2 is 21.1 %. Simulation modelling of the scrap rate in the real-world data set RW_PS shows big differences between the scrap rate of 2.10 % in the optimal allocation of work orders to $Sg_1$ machines, and the non-optimal allocation to $Sg_3$ machines, where the scrap rate is 3.20 %. The difference in scrap rate is 52.4 %.

## 5. CONCLUSIONS

In the presented research work, we have presented a comprehensive simulation study covering simulation modelling of the manufacturing flexibility impact on its sustainable viability. Initially, we identified the research problem of manufacturing flexibility and its characteristics according to a four-level architectural model. The presented classification of the architectural model enables a complete optimisation treatment of the manufacturing flexibility impact on the optimisation level of the manufacturing system. The impact of manufacturing flexibility on sustainable justification is very important, since the classification system is influenced by different sets of parameters, related to environmental, social and financial impacts. Their impact on the manufacturing system is presented and evaluated from the point of view of importance and appropriate use of the optimisation approaches and methods. In the simulation study, these research questions were linked, and evaluated using a self-developed discrete simulation model. The data-driven simulation model incorporates the manufacturing system data obtained using the newly proposed mathematical modelling method. The mathematically generated data allow us to address comprehensively the optimisation problem of optimised manufacturing scheduling, and its relation to manufacturing flexibility and sustainability. The simulation study includes its own proposed block diagram of incorporating a simulation modelling approach of sustainable production eligibility from the point of view of optimising electricity consumption data, and the interdependence of scrap percentage and machine age. The data-driven simulation model is shown in a 3-D Simio environment. Based on the evaluation of the importance of simulation modelling of the Kacem and Brandimarte benchmark datasets, we extended the simulation study to inputs from the real-world production system named RW_PS. The numerical and graphical simulation results obtained proved the high degree of relevance of the optimisation approaches used. The IHKA evolutionary calculation method obtained optimisation results reducing electricity consumption by 10.6 % on average compared to the conventional optimisation approach. The importance of proper optimisation of the scrap rate was evidenced by an average of 36.5 % less scrap using the appropriate IHKA optimisation approach. The optimisation results demonstrate a high degree of manufacturing flexibility dependence, and its sustainable viability. The importance of appropriate production scheduling from a sustainability standpoint is crucial in order to achieve social, environmental and financial goals. The presented results prove that, with the help of the proposed simulation study, it is possible to optimise the manufacturing system in the complex view of a multi-objective optimisation problem. The results of the presented research work prove the importance of the initial research question of the manufacturing flexibility impact on its sustainable viability. In the further phase of the research, it is necessary to remove the limitations in relation to testing so far only the FJSSP type of production on DJSSP and other types of production systems, since their sustainable viability is crucial at the present time.

## ACKNOWLEDGEMENT

This research was funded by the Slovenian Research Agency (ARRS), Research Grant P2-0190.

## REFERENCES


[1] Seng, D. W.; Li, J. W.; Fang, X. J.; Zhang, X. F.; Chen, J. (2018). Low-carbon flexible job-shop scheduling based on improved nondominated sorting genetic algorithm-II, *International Journal of Simulation Modelling*, Vol. 17, No. 4, 712-723, doi:10.2507/IJSIMM17(4)CO18

[2] Ojstersek, R.; Lalic, D.; Buchmeister, B. (2019). A new method for mathematical and simulation modelling interactivity: A case study in flexible job shop scheduling, *Advances in Production Engineering & Management*, Vol. 14, No. 4, 435-448, doi:10.14743/apem2019.4.339

[3] Rosen, M. A.; Kishawy, H. A. (2012). Sustainable manufacturing and design: Concepts, practices and needs, *Sustainability*, Vol. 4, No. 2, 154-174, doi:10.3390/su4020154

[4] Prester, J.; Buchmeister, B.; Palcic, I. (2018). Effects of advanced manufacturing technologies on manufacturing company performance, *Strojniski vestnik – Journal of Mechanical Engineering*, Vol. 64, No. 12, 763-772, doi:10.5545/sv-jme.2018.5476

[5] Fu, H. C.; Liu, P. (2019). A multi-objective optimization model based on non-dominated sorting genetic algorithm, *International Journal of Simulation Modelling*, Vol. 18, No. 3, 510-520, doi:10.2507/IJSIMM18(3)CO12

[6] Li, Y.; Yao, X.; Zhou, J. (2016). Multi-objective optimization of cloud manufacturing service composition with cloud-entropy enhanced genetic algorithm, *Strojniski vestnik – Journal of Mechanical Engineering*, Vol. 62, No. 10, 577-590, doi:10.5545/sv-jme.2016.3545

[7] Joung, C. B.; Carrell, J.; Sarkar, P.; Feng, S. C. (2013). Categorization of indicators for sustainable manufacturing, *Ecological indicators*, Vol. 24, 148-157, doi:10.1016/j.ecolind.2012.05.030

[8] Benjaafar, S.; Ramakrishnan, R. (1996). Modelling, measurement and evaluation of sequencing flexibility in manufacturing systems, *International Journal of Production Research*, Vol. 34, No. 5, 1195-1220, doi:10.1080/00207549608904961

[9] Ojstersek, R.; Buchmeister, B. (2020). The impact of manufacturing flexibility and multi-criteria optimization on the sustainability of manufacturing systems, *Symmetry*, Vol. 12, No. 1, Paper 157, 22 pages, doi:10.3390/sym12010157

[10] Ojstersek, R.; Zhang, H.; Shifeng, L.; Buchmeister, B. (2018). Improved heuristic Kalman algorithm for solving multi-objective flexible job shop scheduling problem, *Procedia Manufacturing*, Vol. 17, 895-902, doi:10.1016/j.promfg.2018.10.142

[11] Pantić, M.; Dordjević, A.; Erić, M.; Mitrović, S.; Babić, M.; Džunić, D.; Stefanović, M. (2018). Application of artificial neural network in biotribological research of dental glass ceramic, *Tribology in Industry*, Vol. 40, No. 4, 692-701, doi:10.24874/ti.2018.40.04.15

[12] Kacem, I.; Hammadi, S.; Borne, P. (2002). Pareto-optimality approach for flexible job-shop scheduling problems: hybridization of evolutionary algorithms and fuzzy logic, *Mathematics and Computers in Simulation*, Vol. 60, No. 3-5, 245-276, doi:10.1016/S0378-4754(02)00019-8

[13] Mastrolilli, M.; Gambardella, L. M. (2000). Effective neighbourhood functions for the flexible job shop problem, *Journal of scheduling*, Vol. 3, No. 1, 3-20, doi:10.1002/(SICI)1099-1425(200001/02)3:1<3::AID-JOS32>3.0.CO;2-Y

[14] Xu, S. Z. (2019). A petri net-based hybrid heuristic scheduling algorithm for flexible manufacturing system, *International Journal of Simulation Modelling*, Vol. 18, No. 2, 325-334, doi:10.2507/IJSIMM18(2)CO6

[15] Meolic, R.; Brezočnik, Z. (2018). Flexible job shop scheduling using zero-suppressed binary decision diagrams, *Advances in Production Engineering & Management*, Vol. 13, No. 4, 373-388, doi:10.14743/apem2018.4.297

[16] Koste, L. L.; Malhotra, M. K. (1999). A theoretical framework for analyzing the dimensions of manufacturing flexibility, *Journal of Operations Management*, Vol. 18, No. 1, 75-93, doi:10.1016/S0272-6963(99)00010-8

[17] Rupnik, B.; Nardin, R.; Kramberger, T. (2019). Discrete event simulation of hospital sterilization logistics, *Technical Gazette*, Vol. 26, No. 5, 1486-1491, doi:10.17559/TV-20180614102011

[18] Warnecke, H. J.; Bullinger, H. J.; Hichert, R.; Voegele, A. (1990). *Cost Accounting for Engineers* (in German: *Kostenrechnung für Ingenieure*), Carl Hansen Verlag, München