

Received September 23, 2021, accepted October 10, 2021, date of publication October 14, 2021, date of current version October 25, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3120126

Energy-Aware Flowshop Scheduling: A Case for AI-Driven Sustainable Manufacturing

MORAD DANISHVAR¹, SEBELAN DANISHVAR¹, EVINA KATSOU¹, S. AFSHIN MANSOURI²,
AND ALIREZA MOUSAVI¹, (Senior Member, IEEE)

¹College of Engineering, Design and Physical Sciences, Brunel University London, Uxbridge UB8 3PH, U.K.

²College of Business Arts and Social Sciences, Brunel Business School, Brunel University London, Uxbridge UB8 3PH, U.K.

Corresponding author: Morad Danishvar (morad.danishvar@brunel.ac.uk)

This work was supported by the Z-FACTOR Project framework, which received funding from the European Union's Horizon 2020 Research and Innovation Program under Grant 723906.

ABSTRACT A fully verifiable and deployable framework for optimizing schedules in a batch-based production system is proposed. The scheduler is designed to control and optimize the flow of batches of material into a network of identical and non-identical parallel and series machines that produce a high variation of complex hard metal products. The proposed multi-objective batch-based flowshop scheduling optimization (MOBS-NET) deploys a fully connected deep neural network (FCDNN) with respect to three performance criteria of energy, cost and makespan. The problem is NP-hard and considers minimizing the energy consumed per unit of product, operations cost, and the makespan. The output of the method has been validated and verified as optimal operational planning and scheduling meeting the business operational objectives. Real-time and look ahead discrete event simulation of the production process provides the feedback and assurance of the robustness and practicality of the optimum schedules prior to implementation.

INDEX TERMS Scheduling, deep neural networks, discrete event simulation (DES), key performance indicator (KPI), operational planning and scheduling (OPS), optimization, hard metal.

I. INTRODUCTION

The desire to find the silver bullet of implementable scheduling solutions in a complex manufacturing environment is persistent. Despite their theoretical and mathematical strength, most scheduling optimization solutions have remained impractical or, at best, highly restricted to excessively controlled environments. However, with significant advancements in machines tools automation, shop floor information management systems, and adaptability of the workforce, a breakthrough is occurring. As the industrial system evolves into the fourth generation known as 'Industry 4.0', more accurate insight into the capabilities and constraints of plants is becoming possible [1]–[3]. Industry 4.0 is widely accepted in the manufacturing industry since it guides a novel and promising production paradigm. The evolution of data-driven system state analysis is encouraging new numerical and logical methods but at the same time implementable. Together, these generate and leverage the concept of 'smart factories' to comprise the next industrial revolution for

manufacturing, characterized by increased flexibility, productivity, efficiency, and sustainability, ultimately ensuring competitiveness in the global market [4], [5].

In today's markets, diversity of demand and competitiveness increases, and manufacturing corporations have to cut out their costs and improve their production line flexibility. However, they face complex scheduling problems in their workshops. Operational planning and scheduling (OPS) in flexible manufacturing systems (FMS) operations is basically a challenging task, and if a decision-making model can evaluate different scenarios based on production constraints and business requirements, it will provide the flexibility needed [6]. OPS involves effective resources allocation (labour, material, equipment) to activities over time in order to satisfy temporal and resource capacity constraints. Moreover, OPS optimizes different objectives by minimizing production cost and makespan whilst maximizing energy efficiency (i.e., minimizing energy consumed per unit of production) and customer satisfaction [7], [8]. The flowshop scheduling or OPS problem, known as a non-deterministic polynomial-time (NP) hard problem, is significantly difficult to optimize by most traditional optimization techniques.

The associate editor coordinating the review of this manuscript and approving it for publication was Ayaz Ahmad¹.

In these methods, performing the optimization algorithm on the particular points on the domain of the target function (e.g., the linear motion between these points) will cause the process to be converged toward the local optimum [9]. Artificial Intelligence (AI) and Machine Learning (ML) [10] techniques have a great place in the OPS domain due to their abilities in dealing with the operational diversity and intrinsic difficulty of most scheduling optimization problems [11]. Schalkoff [12] defined the field of AI in 1990 as follows: “Artificial intelligence includes problem-solving by methods modelled after natural activities and cognitive processes of humans using computer programs that simulate them”.

The motivation of this study is to prove and subsequently capitalize on the new capabilities of Industry 4.0 enabled plants and provide a robust and implementable optimal and effective schedule to maintain the highest production efficiency and productivity. Optimal schedules lead to the faster movement of products (higher productivity) with lower energy consumption (green manufacturing), better use of assets (optimal efficiency) and most importantly, at a lower cost. Even though the application of a robust scheduler is articulated in one complicated use case in this paper, the same solution can be deployed in any batch-based flowshops manufacturing system. The current scheduling tools have predominantly been designed to optimize performance oriented KPIs, such as minimizing makespan and maximizing production rate. Energy-aware scheduling [13] is a new trend to embed sustainability into the production planning stage by explicitly considering energy consumption as a decision criterion in shop floor scheduling. To the best of our knowledge, no commercial tool is available in the market for discrete part manufacturing operations in general and for batch-based flowshop operations in particular. Motivated by the needs of a major discrete part manufacturer in tungsten carbide hard metal manufacturer in Europe that run energy-intensive operations, the current research aims to develop and pilot test a novel methodology for flowshop scheduling considering multiple decision objectives, including cost, makespan, and energy consumption, and to develop a prototype as the proof of concept.

In this study, the case study is a highly complex hard metal like most in real-world general flowshop operations. Due to the shortage of OPS collected from live operation to the Deep Neural Network (DNN) training, a simulation model has been designed and implemented in Arena 2018 simulation package. Simulation modelling is a conventional approach for evaluating the scheduling of a flowshop system; however, it is costly and time-consuming, and design and developing a model and interpreting the results requires expertise [14]. The simulator generates limited random scenarios for scheduling sequences based on various random batch numbers and their related makespan, total cost, energy consumption and other key performance indications (KPIs). These limited scenarios OPSs and KPIs assign as a training dataset to a proposed Fully Connected Deep Neural Network (FCDNN) as a decision-making model to replace the simulation model. FCDNN is

a data-driven approach to OPS problems that does not rely on the traditional prescriptive formulation. NNs are effective and cheaper alternative modelling of flowshop scheduling optimization problems which, due to their robustness, parallelism and ability for optimization, have been successfully deployed.

This study reports on research aiming to develop and pilot test a novel methodology for a Multi-Objective Batch Base Flowshop Scheduling Optimisation using FCDNN (MOBS-NET) that schedule batch jobs for identical and non-identical machines in parallel and series formations and find quick optimal solutions to the flowshop OPS problem that is not possible to meet through the simulation. The main contributions of this research can be listed as follows:

- Design and development of a bespoke data acquisition system to collect critical production data. This is a complex exercise in the industry, and the process of digitization can be replicated and scaled to similar industrial processes and cases (i.e., powder metallurgy)
- Data analytics for combining total production system and co-relating key performance indicators of manufacturing process.

Deploy the FCDNN method to find the optimal production plan by satisfying makespan, total cost, energy consumption objectives. In the following section, we will critically review the literature on scheduling methods. In Section 3, we describe a real-world hard metal use case flowshop with an overview of the framework and some results of the simulation model. In Section 4, we propose the FCDNN model that has been designed to be trained from a combination of collected and a finite number of simulation outputs. This will be followed by a comparison and evaluation of the deployed model's behaviour in the dynamics of the complex operations. Finally, this study is concluded by a discussion of the proposed method application, conclusion and future research direction.

II. RELATED WORK

In the last three decades, extensive research has been dedicated to the pressing problem of how to schedule a production plan to meet all the desired efficiency, productivity, economic, and environmental needs. A plethora of Mathematical [15], Heuristic [16], and AI-inspired [10] methods have been suggested. Despite their significant theoretical and at times, specific practical achievements, to the best knowledge of the authors, there does not seem to be a complete and universally accepted scheduling method. Current solutions and in our own experience with a wide range of industries show that the efficiency of scheduling solutions is marred with inflexibilities that arise from the dynamics of system settings, characteristics, operating conditions, and the ever-changing production objectives [17].

Alternative names given to scheduling methods in the literature are priority rules, scheduling rules, or dispatching rules. Earlier enumerative algorithms provided prescriptive modelling solutions such as linear programming, and later, more advanced techniques such as mixed integer programming

(MIP) were introduced [4], [15]. For instance, [15] applied MIP to analyze the trade-off between minimizing makespan, a measure of service level and total energy consumption.

In the heuristic approach, a problem-specific algorithm is developed. Heuristics scheduling methods, due to their ease of implementation, satisfactory performance, low computational requirement, and flexibility to incorporate domain knowledge are regularly applied in practice [16]. A heuristic approach is a typical way to solve scheduling problems because they are NP-hard. But the inherent weakness of classical Heuristic methods is their reliance on expert judgments, perspective and continuous interference. In the former cases, bias and in the latter inefficiencies make them at times impractical and case constrained (meta-heuristic [18], [19] and hyper-heuristic [20]–[22]). For example, the dispatching rule approach calculates the priority of each job via a set of predetermined dispatching rules (i.e., limitation of expert perspective). The jobs are then processed in order of descending priority. This approach occasionally encounters issues in selecting the optimal dispatching rule because it cannot outperform other rules in every scheduling situation (i.e., inefficiency) [16], [17]. Thus, an optimal universal dispatching rule is absent (i.e., case constrained). To address this shortcoming and to leverage the emergence of big data in manufacturing, a strand of scheduling literature has emerged [23]–[28].

Zarandi *et al.* [11] and Li *et al.* [29] have conducted comprehensive literature reviews on artificial and computational intelligence techniques for scheduling problems and categorized them into five methods of Fuzzy logic [30], Expert systems, Machine learning [31]–[33], Stochastic local search optimization algorithms and modern heuristic algorithms with global optimization performance. Figure 1 shows these AI techniques applied in the scheduling problem.

Despite extensive research workstreams, there is a persisting inflexibility in the scheduling models; they are incapable of absorbing the real uncertainties and the unpredictability of real-time and real-world events. To name a few, quality and quantity changes of demand, changes to the due date, states and condition of the shop floor equipment, machinery, raw material quality fluctuation, etc.

In dynamic scheduling models where one or more conditions like the number of jobs or the number of operation machines are not constant, the problems are under the consideration of multiple objectives, time-dependent processing time and uncertainty [4], [34]. The ML techniques are becoming popular because they can handle NP-Hard problems by learning complex relationships between the input and output variables, which are difficult to express with analytical and heuristic methods in a dynamic manufacturing environment [10], [31], [35]. As examples of these techniques, studies of scheduling sequences by decision trees by [36] and Support Vector Machine (SVM) algorithms by [37]. Other studies used Self-Organizing Maps (SOMs) to indicate adequate dispatching [38]. However, these machine learning methods cannot easily guarantee sufficient prediction

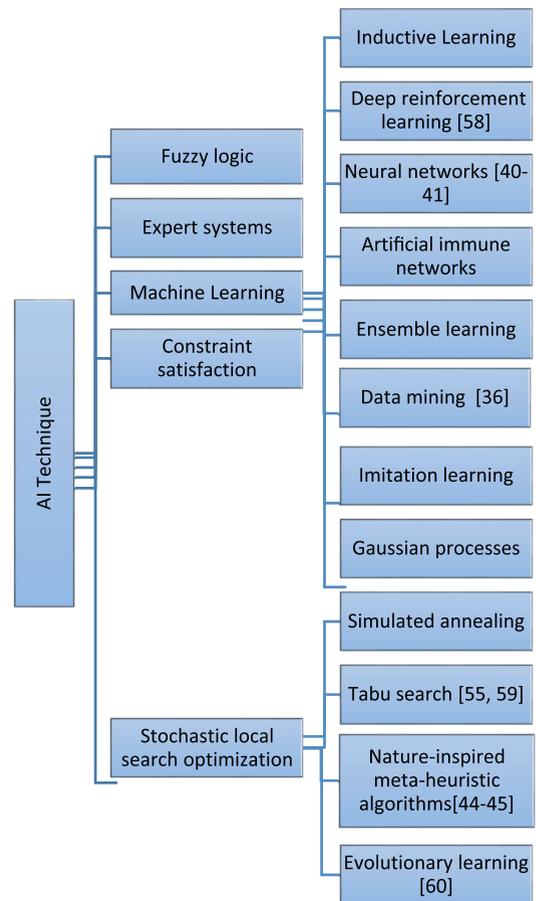


FIGURE 1. AI techniques over intelligent scheduling problem [11].

accuracy and are not suitable for high dimensional data due to the curse of the dimensionality problem.

NNs are one of the AI techniques that have been used to solve complex problems which might do not have any analytical or heuristic solutions. The NNs are a computational model inspired by the biological nerve system and has an outstanding learning ability between input and output patterns of a complex system. The feed-forward NNs are a model used for data collection, pattern recognition, and simulation of various complex systems. Through the use of non-linear data, artificial and deep NNs have better predictive quality due to their excellent learning ability. The ability to learn from examples makes NNs a particularly powerful programming tool when domain rules are not entirely certain or in the presence of inaccurate or conflicting data [39].

Although NN modelling has been employed for scheduling problems in the literature [40]–[42], most of these studies have focused on simple operations flow, which may not incorporate the complexity of real-world operations. Modelling and analysis for the detailed scheduling of complex operations flowshop systems by NN need more attention. With this objective, [14] developed a classical NN model to quickly assess the expected profit, as the main KPI, of different

schedules of flowshop scheduling. The proposed model helps managers estimate the throughput based on historical data with a trained classical NN model instead of a simulation model, which is costly and complex. We borrowed some of the ideas from this study and extended it for a multi-objective flowshop scheduling where multiple KPI's are considered, including machines utilization, energy consumption, operation cost, and settings changes time. Furthermore, the applied NN in this study has a simple structure (since published in 2013) and has a significant difference with the proposed MOBS-NET in our study in the layout and performance.

The recent examples of improved NNs methods in production scheduling and objective optimization are the application of Long-short term memory (LSTM) in [10], Artificial NN in [39], DNN in [40], and Convolutional NN in [40]. Recently, hybrid techniques that involve searching strategies that navigate heuristic algorithms in the problem domain away from local optima have been applied, such as hybrid neural network–genetic algorithm [41].

Kim *et al.* [40] studied machine allocation in a semiconductor fabrication production scheduling problem with an automated material handling system's constraint. A DNN-based scheduling algorithm to solve the problem has been proposed, and a small-sized experiment was simulated to address a machine targeting problem. This study claims that the proposed method could improve the productivity KPI (throughput and machine utilization) of each workstation. Despite some similarities of this study with our proposed method in data preparation and collection, but there are some differences in the selected objective KPIs and applied DNN layout with the proposed MOBS-NET. For instance, energy consumption has not been selected as a decision criterion in shop floor scheduling in this research.

The makespan of the orders depends on several factors, including arrival rate of material, variability of material/production process, and the batch sizes. Some manufacturing systems deploy batch processing procedures to avoid cumbersome setups, stoppages and to facilitate material handling. A batch is defined as a group of jobs that have to be processed jointly, and a batch scheduling problem consists of grouping jobs on each machine into batches that are scheduled either in serial or in parallel. They can be classified into static and dynamic scheduling [42]. In our experience with multiple plants, we have realized that batch size is an important parameter that affects makespan (directly) and scheduling (indirectly) of an FMS. Literature suggests meta-heuristic evolutionary learning methods such as Genetic Algorithm (GA) or nature-inspired meta-heuristic algorithms such as monarch butterfly optimization (MBO) [43] or elephant herding optimization (EHO) [44] algorithm as useful approaches to deal with scheduling challenges [45]. A good scheduling method can use the ability of batch processing machines (BPMs) efficiently to achieve expected performance while satisfying the constraints of batch size and other properties, i.e., grouping jobs into batches before applying a scheduling rule [46]. In recent years, there have been many

studies on BPMs scheduling problems in different manufacturing processes.

Due to the complexity of solving batch scheduling sequences in a real-world flowshop (for more than two-stage flowshops), there is no mathematical function to analyze a stochastic model for these problems. Therefore, computer simulations or AI methods can be employed to deal with the complexity of this kind of complex and non-linear problem. In this approach, different sequence combinations can be considered for processing different jobs with different specifications (e.g., processing time). Hence, different sequence combinations lead to different makespan, cost or KPIs (e.g., energy consumption and quality) as the outputs of the simulation or trained AI model. An excellent example of a research study on batch grouping and scheduling was conducted by [16]. A clustering algorithm has been designed to group similar jobs under machine capacity constraints and then applied a scheduling rule selection model based on a classical NN for batch sequencing. Furthermore, two different computer simulations based on network modelling (visual SLAM language software) and Discrete Event Simulation (DES) (Arena 12 simulation software), which were designed to solve the batch grouping and scheduling problems, respectively, are discussed in [14] and [47]. Noteworthy, the proposed MOBS-NET in this study offers significant insight into the grouping of the batches.

All reviewed literature has been applied in one or a combination of various platforms such as single machine [48], parallel machine [49], flow shop [8], series batch [50], [51], real-time [20], and flexible manufacturing systems scheduling [52]. Between these, the parallel machine scheduling (PMS) problem is an atypical scheduling problem with extensive practical relevance. The solution approach to the PMS problem mainly includes heuristic algorithm, and AI method such as EA and NNs have been widely studied to solve the problem with the objective of minimizing the makespan [15], [53]–[55].

With reference to the reviewed literature on the weakness and strengths of different production scheduling and objective optimization techniques, batch grouping, as well as PMS problems, the proposed alternative MOBS-NET is presented in the following section.

III. PROBLEM DESCRIPTION AND DATA PREPARATION

In this section, a real-world case study in a tungsten carbide hard metal corporation will be reviewed.

A. CASE STUDY

A Tungsten carbide hard metal corporation is an intensive user of precision grinding, milling and turning operations, particularly for the final stages of hard metals (WC-Co) wear tooling for numerous industrial applications. Surface finishing, including surface roughness, dimensional tolerances and structural integrity, must meet precise standards which demand continuous measuring and quality control. The non-quality is very costly at this stage since the production process

is based on powder metallurgy. The recycling process must then be made through the chemical dissolution of the parts to recover the starting powders. The production strategy is MTO, and the process is included three productions' cell'. The production details are as the following.

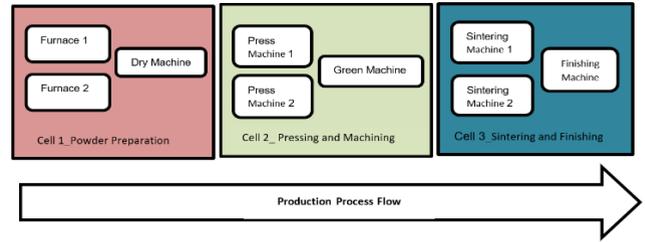


FIGURE 2. Production flowshop.

TABLE 1. Product raw material contents.

Product name	P1	P	P3	P4
Powder usage	RM1: 1 kg	RM2: 3 kg	RM1:1kg, RM3:1 kg	RM2: 2kg, RM4: 2 kg

TABLE 2. Machine electrical consumption.

Machine Name	Furnace 1	Furnace 2	Dry machine	Press Machines	Green machine	Sintering machines	Finishing Machine
Running cost (£) /hr	10	20	30	40	25	70	50
Electrical power usage (KW/hr)	50	60	20	10	15	25	10

- Cell 1 includes powder preparations in two non-identical furnaces and dry machine; the prepared powder enters cell 2 for pressing with two identical machines to build the products and then enters to green machining to precision machining. The product then moves to cell 3, which includes two identical sintering and a finishing Machine. Figure 2 shows the production process flow.
- There are four products (P1 to P4) with the presented raw material (RM) usage in Table 1. RM contains RM1, RM2, RM3 and RM4 and cost £50, £60, £65, and £70 per kilogram, respectively.
- Furnaces 1 and 2 have a capacity of 10 and 15 kg (20% overload is acceptable) and need to run for 10 hrs and 20 hrs (plus 4 hrs for warming up) respectively to cook and prepare the raw materials.
- The dry machine has a capacity of a maximum of 15kg and takes 8 hrs to dry and dehumanize the raw material and make the final powders. Three operators work for furnace and dry machine.
- Press machine 1 and 2 press the powders for products P1 to P4 in 15, 45, 30 and 60 minutes, respectively. Set up a time for each machine is 15 minutes. Press machine causes defect type 2 over 1% of products.
- Green machine cuts and machines the products are coming out of press machines. For products P1 to P4 in 1, 2, 1.5 and 2 hours respectively. Set up a time for each machine is 30 minutes. Green machine causes defect type 3 over 1% of products.
- Two sintering machines sinter the products in 1hrs for lighter than 2kg and 1.5hrs for heavier products. The defect cost in this machine is 10% of product cost to recycle and recover the powders. Finishing the products last 2 hours and machine set up time is 15 min. 70% of whole defects occur in this stage which is called tolerance defect (type 4). Defects in this line are non-recyclable and should be sold to the scrapyard with 2% of their raw material weights.
- Overall, six operators are available for pressing, green, sintering and finishing machines.
- Each shift is 7 hrs work plus an hour break (8 hrs overall).
- Furnaces and Machines running costs (including labour, electrical power, depression and maintenance but excluding raw material cost) and Electrical power usage are presented in Table 2.
- Electricity cost rate is: 5p/kWh

B. DATA ACQUISITION AND PREPARATION

A detailed shop floor data collection solution was implemented to collect the required data for OPSs and KPIs. We implemented a digital material tracking and traceability

solution that followed the product throughout the production pathways. In addition, we developed an efficient real-time data acquisition platform to collect live data in the process. It included a combination of automatic data acquisition, e.g., sensors, actuation, machine states, and operator availability, as well as a simplified digitalized manual data acquisition (e.g., Human Machine Interface panels) connected within a shopfloor Control Area Network (CAN) and SCADA. Furthermore, operational data was also automatically and directly queried from the proprietary enterprise data management system (in this case, the SAP platform). Further contextual intelligence was gathered through interviews with production and accounting managers. The collected dataset was limited to ten regular orders and wasn't sufficient for the training of the proposed FCDNN model. For this purpose, a Mont Carlo simulation of the use case has been designed and implemented in Arena simulation to generate a reliable and larger amount of dataset.

C. DES SIMULATION AND MODELLING

The DES simulation is used in this study used to generate a reliable and sufficient number of scenarios for the training and validation of the proposed MOBS-NET method. Based on the availability and accessibility of accumulation of live production data and manufacturing information from

the shopfloor, DES simulation of the use case was designed and modelled in Arena 2018 simulation and modelling package. DES is an effective tool for the analysis of system performance, system monitoring, prediction and scheduling problems [58]. DES has also shown to outperform other analytical or physical models capturing the complexities of manufacturing systems [59].

The simulation details are not objective of this research study; see more details in [60], [61]. To create a steady-state analysis and to statistically validate the DES models of optimum scheduling solutions, the following assumptions have been made in consultation with the production management team at the plant, it was agreed that: (1) the transfer time between machines are ignorable (cellular layout), (2) jobs are prepared for processing at the machine release times (sufficient material buffer), (3) the total manufacturing cost calculation excludes raw material cost, and (4) the machine capacity is one item per cycle, except for the two furnaces which can be loaded up to their maximum capacities.

In the end, the simulation model has been compared and validated through 10 direct collected scenarios and also in consultation with the production management team. The scenarios were collected based on a regular order which is a batch size of 20 from various products (P1, . . . , P4).

An example of the direct collected OPSs from shopfloor is in Appendix I. Appendix I includes the OPS for all the machines in the process line (the batch and machine numbers for the parallel furnaces and machines, starting and leaving process times for all the machines). Moreover, Appendix II presents the manufacturing KPIs including machines utilizations, machines energy consumption, machines operation cost, and settings changes time. These KPIs are the simulation outputs for the collected scheduling in Appendix I (approved by the production management team).

As explained above, the simulation purpose is to generate a larger dataset for the training of the proposed method. However, implementation of all these possible scenarios in the simulation is time-consuming and costly; therefore, a total of 300 various scenarios (including ten direct collected) have been prepared. The operational planning, scheduling and KPIs will be used in training and validation of the proposed NN method in the following section.

Table 3 presents four production scenarios with the minimum total cost, energy consumption, quality and makespan from 300 simulated scenarios. There are two approaches to find the production plan for a specified period and defined decision objectives of the total cost, makespan, and total energy consumption. The first approach is to run the simulation for a long period and detect the best solution. The second approach is to train a model with the known scenarios and monitor the patterns of model inputs (e.g., machines cycle time, batch size, machine capacity and numbers), and find their correlations/impact on the system outputs (e.g., cost, makespan and energy consumption).

In the following section, we will propose an FCDNN model to find the pattern and inter-relationship between the

OPSs and the corresponding KPIs to meet the customer's ideal cost and makespan as well as the manufacturer's constraints in energy consumption.

IV. FULLY CONNECTED DEEP NEURAL NETWORKS (FCDNN)

NN algorithms are extensively used by machine learning and data scientists for solving different kinds of data regression and classification problems [62]. In this research study, three NN regression models will be built for each cell to find the OPS which meet the customer's ideal cost and makespan as well as the manufacturer's desired energy consumption.

Artificial Neural Networks (ANN) has proven in many applications to be a robust data modelling tool capable of capturing and representing complex input/output relationships. They are a human brain-inspired programming paradigm that allows a computer to learn from observational data similar to the brain. Fully connected networks are 'Structure Agnostic' and the subcategory of deep neural networks [63]. DNNs have been shown great success in various tasks like nonparametric regression and classification.

Numerous research has explained the reasons for the great success of this method in practical applications and filled the gap between practical use and theoretical Understanding [64]. A fully connected deep neural network (FCDNN) consists of a series of fully connected layers that connect every layer neuron to the others in another layer. The structure of the proposed FCDNN developed for this study is represented as follows in Figure 3.

A. FCDNN STRUCTURE

The FCDNN used in this study has a five-layer network structure, consisting of an input layer, three hidden layers, and an output layer, each composed of a plurality of neurons that can be calculated in parallel. The connection between the hidden layers and between the first hidden layer and the input layer are connected by an activation function. The details of the structure of the proposed FCDNN are as following:

1) FULLY CONNECTED LAYER (OR DENSE LAYER)

The fully connected layers are able to learn non-linear combinations of input features considerably efficiently. Neurons in a fully connected layer have full connections to all activations in the previous layer. Their activations can hence be computed with a matrix multiplication followed by a bias offset [65].

$$H(x) = Wx + b \quad (1)$$

where $W \in R^{(K,n)}$ is weight matrix and $b \in R^K$ is the bias offset.

2) ELU ACTIVATION LAYER

Exponential Linear Unit (ELU) is a function that tends to converge cost faster and generate more accurate results [66].

$$\text{ELU}(x) = \begin{cases} \alpha(\exp(x) - 1), & \text{if } x \leq 0 \\ x, & \text{if } x > 0 \end{cases} \quad (2)$$

TABLE 3. Some Scenarios with a minimum total cost, makespan and total energy consumption.

Scenario no.	Makespan (hrs)	Total cost (£)	Number and Type of Defected Product(s)	Total Energy Consumption (KWh)
97	179	6422	No defect	5654
116	160	7374	No defect	5255
30	158.25	8080	No defect	5380
267	157.5	6459	1 type 2	5958.63

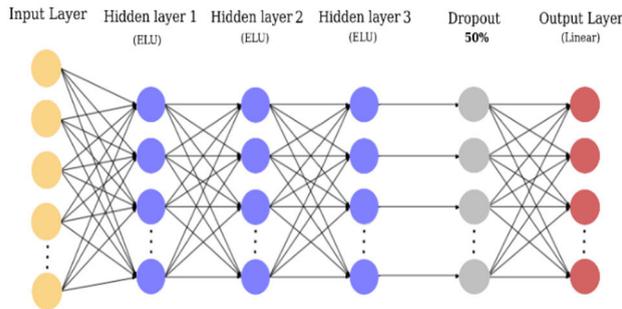


FIGURE 3. Proposed FCNN with multiple hidden layers and a dropout layer.

ELU uses the activation function to achieve mean zero, as the learning can be made faster. For the ELU activation function, an α value is picked; a common value is between 0.1 and 0.3. Hence it is a good option against activation functions like ReLU (Rectified Linear Unit) since it decreases the bias shift by pushing the mean activation towards zero. Unlike ReLU, ELU can produce negative outputs.

3) DROPOUT LAYER

Dropout is a sort of regularisation that randomly drops some proportion of the nodes that feed into a fully connected layer. Dropping a node means that its contribution to the corresponding activation function is set to zero, and therefore it prevents the network from memorizing the training data (overfitting). With dropout, training loss will no longer tend rapidly toward zero, even for very large deep networks.

4) LINER ACTIVATION LAYER

A linear activation function takes the form [63]:

$$A = cx \tag{3}$$

where c is a constant number and activation is proportional to the input. This way, it provides a range of activations, so it is not binary activation.

B. LOSS AND OPTIMIZATION FUNCTIONS

In most learning networks, the error is determined as the difference between the actual output and the predicted output [57].

$$J(w) = p - \hat{p} \tag{4}$$

where J is a function of internal parameters of model, i.e. weights and bias. The function that is used to compute this error is known as Loss Function.

Different loss functions will provide different errors for the same prediction, and therefore have a considerable effect on the performance of the model. One of the most widely used loss functions is Mean Absolute Error (MAE) that is used in this research, which calculates the absolute of the difference between the actual value and predicted value. Various loss functions are used to deal with different type of tasks, i.e., regression and classification.

For accurate predictions, minimization of the calculated error functions is needed. In a NN model, the weights and biases are modified using a function called optimization function. Some important first-order optimization functions are Adaptive Moment Estimation (Adam), Stochastic Gradient Descent, and Adagrad [67]. It also calculates a different learning rate. Adam works well in practice, is faster, and outperforms other techniques and is used in this paper with a learning rate set to 0.01.

C. THE IMPLEMENTATION OF THE PROPOSED FCNN

The simplified production process flow shown in figure 2, consists of three cells which each cell begins with two parallel furnaces or machines and continue with a series machine. The first cell includes two non-identical furnaces with different capacities and process time, and then raw material enters a drying machine. The second cell starts with two parallel identical press machines, and then the pressed products go to the green machine and at the end in the third cell, pressed, and machined products enter to either of the parallel identical sintering machines to be sintered and then to the finishing machines for precision quality.

For this experiment, the proposed architecture consists of three similar FCNNs (Figure 3) for three cells and several hyperparameters that should be determined, including the number of fully connected layers, the number of nodes in fully connected layers, dropout, etc. Choosing the number of hidden layers and nodes in hidden layers depends upon the use case and problem statement that we are dealing with. The introduction of the hidden layer(s) makes it possible for the network to exhibit non-linear behaviour. The uncaused increasing hidden layers and the number of neurons would increase the complexity of the model. Choosing hidden layers such as eight, nine, or more may sometimes lead to overfitting.

The presented network settings in Table 4 are set after several comparative experiments, which shows that this combination produces the best performance for all three networks. Hidden layers (dense layers) 1 to 3 are features extraction, the ELU layer is added at the end of every dense layer for accelerating the training speed, and the dropout layer is added after the third dense layer to avoid the extraction of redundant features and to prevent over-fitting, a challenge in deploying deep neural networks to applications [68].

TABLE 4. FCDNN layer types, Output shapes and parameters numbers.

Layer (type)	Output Shape	Parameters number
Hidden layer 1 (Dense)	(None, 70)	4130
ELU 1	(None, 70)	0
Hidden layer 2 (Dense)	(None, 60)	4260
ELU 2	(None, 60)	0
Hidden layer 3 (Dense)	(None, 50)	3050
ELU 3	(None, 50)	0
Dropout 1	(None, 50)	0
Output (Dense)	(None, 50)	2040
Linear 1	(None, 40)	0

1) MODEL STRUCTURE

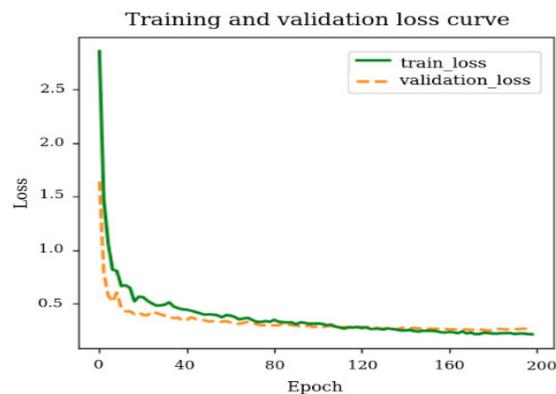
There are 300 scenarios collected from the simulator. The input for each FCDNN is a cluster of cell costs, finishing time and the number of products from each type (Categorical data). After gathering all data and encoding categorical data to numbers, the final input vector dimension is (58×1) .

The output vector dimension is (40×1) that denotes the machines number (for parallel machines) and starting process time for every single product. As we mentioned earlier, the structure of FCDNN for all three cells are the same. Before training, a normalization process has been applied to re-scale the data to $[0, 1]$ in order to diminish the data redundancy and progress data integrity.

2) TRAINING DATASETS

Training a NN is the process of finding the values for the weights and biases. The training of a NN model is most challenging because it requires solving two difficult problems at the same time; learning and generalizing. Learning the training dataset is intended to minimize the loss function while generalizing the model performance allows predictions on test examples (validation dataset). The dichotomy of learning models is that if it learns well, it could be at the cost of generalization (i.e., overfitting), and if a model generalizes well, it may lead to underfitting. One of the objectives in training a NN is to obtain a good balance between these two problems.

In this experiment, the existing 300 scenarios are randomly split into a training dataset (typically 80 per cent of the data), a validation dataset (10 per cent of data) and a test dataset (the remaining ten per cent, usually this been named validation of the model in non-neural network research domains). After training is completed, the trained model's weights and biases will be applied and tested on the test dataset. One of the significant difficulties when working with NNs is overfitting. Model's overfitting often occurs when the training algorithm runs too long. The validation helps to find when

**FIGURE 4. The loss changes and convergence during training for cell1.**

model overfitting starts to happen by keeping the model parameters when the validation error is lowest during the training. Figure 4 shows the training and validation data loss curve for predicting the cell 1 network parameters after 200 epochs. The training process is carried on the other two cells as well. The results show the proposed model addresses the dichotomy of learning and keeps the balance between learning and generalization.

3) MODEL DEPLOYMENT

Three distinctive trained FCDNN models for the three cells, deployed in this section to predict the machine numbers in the parallel process as well as starting process time for each cell in unseen scenarios (named validation) dataset. The series machines (i.e. dry machine, green machine and finishing machine) scheduling have not been predicted through this model since, in the series production process, it has been assumed the first output enters the next series machine. Appendix III presents the predicted scheduling and machine numbers for the three cells in a randomly selected sample scenario in which its machine OPS and KPIs are presented in Appendix I and II, respectively. Figure 5 compares the actual and predicted starting process time of all three cells on random sample scenario (See Appendix I and III) Starting process times of each cell have been chosen as the trigger of scheduling events of the cell, and the start event of subsequent processes in downstream cells are based on parts leaving the previous process (contiguous process). The results reveal that some divergence between actual and predicted scheduling of cells occurs for each order number. For instance, while the actual starting process time for order no.5 in cell 1 is 56 hours, but the model estimates it to be hour 32 hours. This divergence is somewhat inevitable because of the nature of the NN models and can be reduced by increasing the number of training datasets. Although increasing the number of scenarios means more direct sampling or simulation runs which are time-consuming and costly. The authors have chosen 300 scenarios since the model can be validated and tested with 30 scenarios (ten per cent of the dataset). Furthermore, these divergences are not evidence of the model flaw in predicting

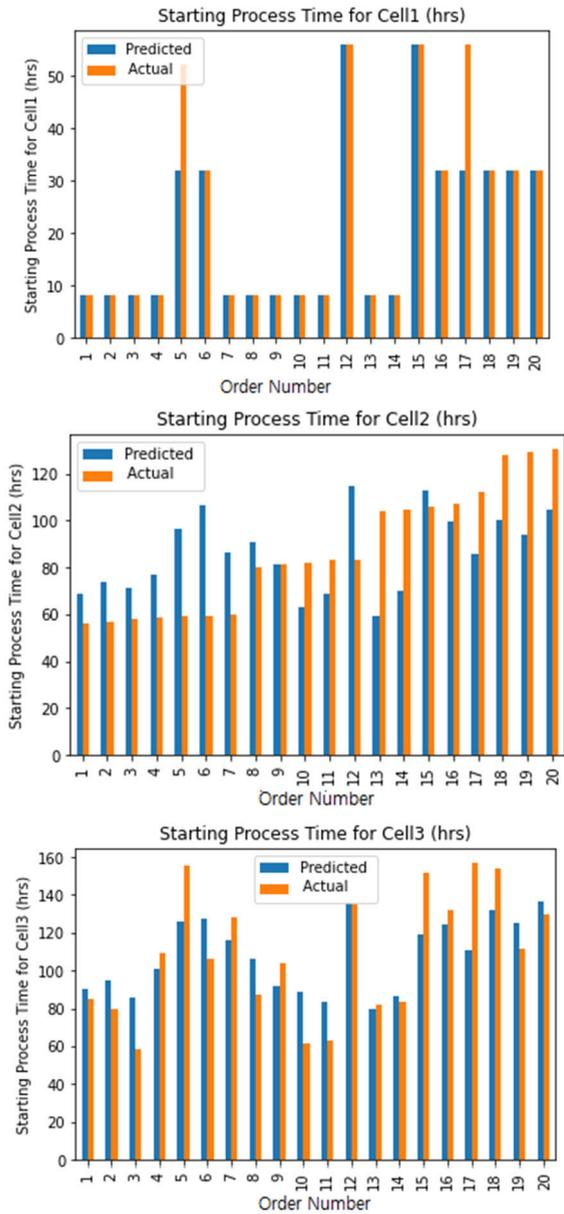


FIGURE 5. Comparison of the actual and predicted scheduling of three cells on the selected scenarios.

the OPS. Any logical and practicability flaw in the new OPC will be identified when the process simulator calculates the values of the process KPIs.

In the following section, the predicted OPSs from the proposed FCDNN model is fed to the DES for the purpose of predicting the values KPIs in look-ahead mode. This novel approach allows the scheduling solution to be verified into a near accurate computer simulation of the plant. Avoiding any disruption and disturbance to the actual system. Moreover, it allows the operation managers to visualize and assess the efficacy of the scheduler prior to implementation.

V. VALIDATION AND COMPARISON

The proposed FCDNN performance in calculating the process OPSs is compared with the actual OPSs on the test

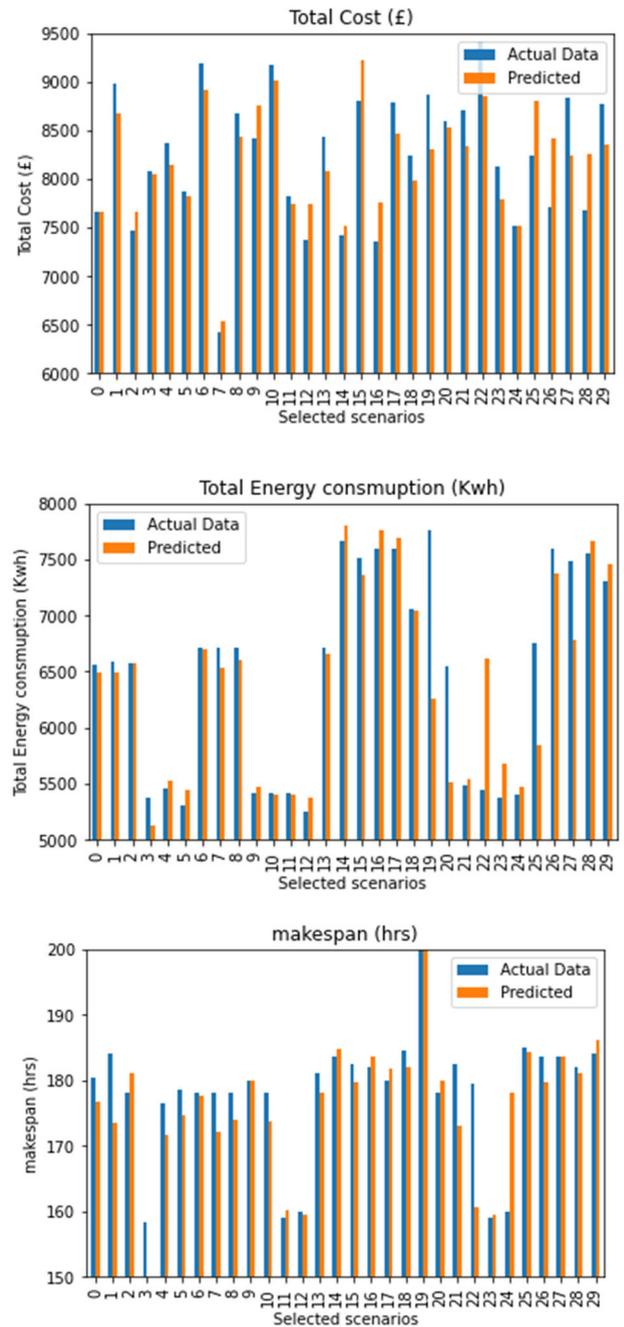


FIGURE 6. Comparison between the actual and predicted objective KPIs for the test dataset.

dataset in this section. As discussed before, ten per cent of the existing 300 scenarios (i.e., thirty scenarios) hasn't been trained for the final validation purpose. These scenarios' selected KPIs, i.e., energy consumption, cost of each machine, plus final Markesan, have been presented in Appendix IV. The proposed model takes these KPIs as inputs and calculated the operational planning (machines number and batch numbers) and machines scheduling as a sample is presented in Appendix III.

In this section, the estimated OPSs fed to the simulator to predict the KPIs for the machines (and cells) in Appendix V. These objective KPIs comparison between total actual and predicted KPIs on the test dataset (thirty scenarios) are shown in Figure 6 in three distinctive charts of the total cost, makespan and total energy consumption. The MAE (Mean Average Error), average deviation and t -Test between these parameters are compared in Table 5. The comparison methods have been chosen because of their extensive applications in the observations' comparison domain. The purpose of the applied paired T-test (two-tailed) is to assess whether the mean scores from two paired thirty actual and predicted KPIs in the test dataset are statistically different from one another. The results present that the proposed FCDNN method regarding the number of model's inputs and outputs and training dataset volume (240 scenarios) has met the manufacturer's satisfying accuracy of under %4 deviations of estimated KPIs.

The performance of the proposed FCDNN method is compared with the two most popular data mining and ML [69] methods. Random Forest Regression and single hidden layer NN methods (with 100 hidden neurons and ReLU active transfer function) were chosen due to their accuracy and applications in similar industrial experiments. Both models are trained with the same training dataset, and the outputs between the actual and predicted KPIs on the test dataset are shown in Table 6. In comparison, FCDNN performs better accuracy due to the more advanced and extensive architecture. However, in the training algorithm's speed and computational complexity, the single-layer NN is faster and less complex to implement.

In the following section, the application of the proposed method in the optimal OPSs calculation will be discussed. Furthermore, minimum final production cost, makespan and energy consumption for the regular order will be reviewed.

VI. DISCUSSION

In a general flowshop environment, dynamism and complexity of operations enhance the need for an accurate model prediction. The dilemma of the businesses is manufacturing with minimum costs, makespan, defects and energy consumption. As discussed in Section III.C, the presented four scenarios in Table 3, which have the minimums, do not prove that they are optimal solutions or have the overall minimums KPIs. There are two approaches to find the optimal solution(s); 1) collection of thousand scenarios (direct collection or through the validated simulator) and find the optimal(s) between them or 2) build a representative function model to generate the optimal OPSs. In Section 4, an FCDNN model proposed based on NN's predictive ability to generate the scenarios. The proposed model acquires the KPIs as the inputs and generates the OPS, i.e., details of operational plans and schedules to meet the KPIs. And finally, for validation of the proposed model, the generated OPSs applied to the simulator and the calculated KPIs compared with the actuals KPIs on a test dataset in Table 7.

TABLE 5. MAE, average variation and T test between the actual and predicted parameters on the test dataset with the proposed FCDNN.

	Total cost (£)	Makespan (hrs)	Total Energy Consumption (kwh)
MAE	299.6	4.03	266.251
Average deviation	%3.6	%2.2	%4.02
t-Test	0.46	0.087	0.295

TABLE 6. MAE, average variation and T-test between the actual and predicted parameters on the test dataset with single hidden layer NN and Random Forest methods.

	Total cost (£)	Makespan (hrs)	Total Energy Consumption (kwh)
<i>Single hidden layer NN</i>			
MAE	740.4	10.2	523.24
Average deviation	%7.9	%8.1	%11.02
t-Test	0.93	0.242	0.524
<i>Random Forest method</i>			
MAE	623.2	9.7	519.35
Average deviation	%6.4	%7.5	%10.83
t-Test	0.89	0.219	0.486

TABLE 7. Some scenarios with minimum total cost, Makespan and energy consumption.

Test	Makespan(hrs)	Total cost (£)	Energy Consumption (KWh)	Makespan deviation (%)	Total cost deviation (%)	Energy Consumption deviation (%)
1	158	6500	5300	4.2	4.5	3.6
2	157	6450	5250	6.9	6.4	5.7
3	156	6400	5200	8.1	8.2	10.2
4	155	6350	5150	10.5	8.8	16.9

To find the optimal solution(s) of this multi-objective problem, a deviation test is conducted. In this test, the less than minimums of makespan, total cost and energy consumption (Table 3) were fed into the proposed model, and the resulting calculated OPSs were tested in the simulator. The deviation results (in Table 6) show if the KPIs are reduced from Test 1 to Test 4, the deviation increases. In other words, there is no specific single optimal solution, and the production manager will be informed of the possible "no single optimum solution". At this stage, an intuitive decision-making exercise based on business priorities and local regulations (e.g., regulation in

TABLE 8. Sample scenario in the Arena simulation package for operational planning and scheduling of the machines in the production line.

Num Order	Product Type	Furnace Processes			Dry Machine			Presse Machine			Green Machine			Sintering Machine			Finishing Machine	
		Machine Number	Batch Number	Starting Process Time	Leaving Process Time	Sarting Process Time	End of Process time	Machine Number	Starting time (before setting change if needed)	Leaving Process Time	Starting time (before setting change if needed)	End of Process time	Machine Number	Starting time	Leaving Process Time	Starting time (before setting change if needed)	End of Process time	
1	1	2	1	8	32	32	40	56	56.75	83.5	84.5	1	85	86	104	106		
2	2	2	1	8	32	32	40	56.75	57.75	63.25	65.75	1	80	81.5	82.5	84.75		
3	3	1	1	8	22	32	40	57.75	58.5	56.75	58.75	1	58.75	59.75	59.75	62		
4	4	2	1	8	32	56	64	58.5	59	106.5	109	1	109	110.5	128	130.25		
5	1	1	3	56	70	104	112	59.5	59.5	154	155.5	2	155.5	156.5	176.00	178.25		
6	2	1	2	32	46	56	64	59.75	60.75	111.5	114	1	106.5	108	110.5	113		
7	4	2	1	8	32	56	64	59.75	60.75	111.5	114	1	128	129.5	132.5	134.75		
8	3	2	1	8	32	56	64	80	81.25	85	87	2	87	88	106	108.25		
9	1	2	1	8	32	56	64	81.25	82.25	87	88.5	2	104	105	108.25	110.5		
10	2	1	1	8	22	32	40	82.25	83	58.75	61.25	2	61.25	62.75	62.75	64		
11	3	1	1	8	22	32	40	83	83.5	61.25	63.25	2	63.25	64.25	80	82.25		
12	4	1	3	56	70	104	112	83.5	84.5	133	135	2	135	136.5	154.25	156.5		
13	3	1	1	8	22	32	40	104	104.75	80	82	2	82	83	84.75	87		
14	1	1	1	8	22	32	40	104.75	106	82	83.5	1	83.5	84.5	87	89		
15	2	1	3	56	70	104	112	106	107	135	137.5	1	132	133.5	152	158.75		
16	4	2	2	32	52	80	88	107	107.75	130	132	2	157	158	178.25	180.25		
17	1	1	3	56	70	104	112	112	112.5	155.5	156.5	2	154	155	158.75	161		
18	3	2	2	32	52	80	88	128.25	129.5	152	154	2	111.5	113	130.25	132.5		
19	2	1	2	32	46	80	88	129.5	130.5	109	111.5	1	130	131.5	131.5	132.5		
20	4	1	2	32	46	80	88	130.5	131	128	130	1	130	131.5	131.5	132.5		
effect Typeeffect Type																		

GHG emissions) could allow the decision-maker to select one solution from a number of alternative solutions. This is still significant assistance to continuous improvement in operations and decision making to meet business and legal objectives in production systems.

VII. CONCLUSION

This study proposes MOBS-NET framework to solve the batch base production flowshop scheduling problems in live real-world complex manufacturing production systems. The experiment in this study is from hard metal use case flowshop, where sequences of a wide variety of jobs are processed in

TABLE 9. Sample scenario in Arena simulation package for the main KPIs of the machines in the process line.

Machine	Utilization	Energy Consumption (Kwh)	Total Cost (£)	Setting change time (hours)
Furnace 1	0.319	2100.00		12
Furnace 2	0.25	2440.00		4
Dry Machine	0.26	640.00		0
Press Machine 1	0.113	132.00		3.75
Press Machine 2	0.245	0.00		0
Green Machine	0.453	325.00		7.5
Sintering 1	0.157	325.00		0
Sintering 2	0.377	335.00		0
Finishing Machine	0.45	265.00		3
Furnace 1			540	
Furnace 2			880	
Dry Machine			982	
Press Machine 1			492.5	
Press Machine 2			0	
Green Machine			982	
Sintering 1			630	
Sintering 2			840	
Finishing Machine			2315.7	
All		6562.00	7662.20	30.25
Variables Used in the simulation				
Weight limit in queue to launch Dry Machine				
% of chance to process the same type of entity than previously if one is waiting				
% of chance to process the same type of entity than previously if one is waiting				

identical and non-identical machines. The machines operate in parallel and series, forming complex routing production process plans. Any change in the production plan, resource schedules, job sequences, or formation of batches (i.e., OPS) lead to different cost, makespan, and energy consumption as the chosen KPIs by our operations managers in the plant. This problem is NP-hard.

The accumulation of shopfloor real-time data, as well as a finite number of scenarios of a verified DES model, have been used to train the FCDNN model. Once the proposed model trained, it will be used to generate OPSs of the complex production lines. It will be able to capture the underlying relationship between input and output variables and consequently build the optimal OPSs based on the optimal KPIs. Therefore, complex simulation settings can be replaced by the proposed FCDNN. The results of the proposed model proved statistically equivalent to the results provided by the verified discrete event simulation model.

This decision support model can help decision-makers evaluate possible OPS and make the best decision automatically and without the intervention of experts. This model adds flexibility and convenience for managing the hard and complex operations of day-to-day production systems and sustain continuous optimal production settings.

TABLE 10. Sample of estimated operational planning and machine schedulings by the proposed method.

Num Order	Product Type	Furnace Processes			Dry Machine		Press Machine		Green Machine		Sintering Machine		Finishing Machine			
		Machine Number	Batch Number	Sarting Process Time	Leaving Process Time	Sarting Process Time	End of Process time	Machine Number	Starting time (before setting change if needed)	Leaving Process Time	Starting time (before setting change if needed)	End of Process time	Machine Number	Starting time (before setting change if needed)	Leaving Process Time	End of Process time
1	1	2	1	8	32	68.5	69	1	68.5	69	89.98	90.98	1	89.98	90.98	
2	2	2	1	8	32	73.8	75	1	73.8	75	94.95	95.86	2	94.95	95.86	
3	3	1	1	8	22	71.1	72	1	71.1	72	86.00	87.50	1	86.00	87.50	
4	4	2	1	8	32	76.8	78	1	76.8	78	100.54	101.54	1	100.54	101.54	
5	1	1	2	32	46	96.6	97.1	1	96.6	97.1	125.67	126.67	2	125.67	126.67	
6	2	2	2	32	46	106.3	107	1	106.3	107	127.51	128.48	2	127.51	128.48	
7	4	2	1	8	32	86.3	87.5	1	86.3	87.5	115.84	116.55	2	115.84	116.55	
8	3	2	1	8	32	90.5	91	1	90.5	91	106.28	107.39	2	106.28	107.39	
9	1	2	1	8	32	81.0	81.25	1	81.0	81.25	91.99	92.99	2	91.99	92.99	
10	2	1	1	8	22	62.8	63.3	1	62.8	63.3	88.81	89.81	2	88.81	89.81	
11	3	1	1	8	22	68.5	68.6	1	68.5	68.6	83.22	84.22	2	83.22	84.22	
12	4	1	3	56	70	114.5	115	1	114.5	115	135.80	136.90	2	135.80	136.90	
13	3	1	1	8	22	59.2	59.8	1	59.2	59.8	79.66	81.36	1	79.66	81.36	
14	1	1	1	8	22	69.9	80	1	69.9	80	86.68	88.08	2	86.68	88.08	
15	2	1	3	56	70	113.0	114	1	113.0	114	124.55	125.60	2	124.55	125.60	
16	4	2	2	32	52	85.7	85.9	1	85.7	85.9	110.41	112.41	2	110.41	112.41	
17	1	1	2	32	52	100.5	101	1	100.5	101	132.31	133.41	2	132.31	133.41	
18	3	1	2	32	52	94.1	94.9	1	94.1	94.9	124.90	125.07	2	124.90	125.07	
19	2	1	2	32	52	104.4	104.75	1	104.4	104.75	136.61	138.31	2	136.61	138.31	
20	4	1	2	32	52			1					2			

The primary objective of this study was to demonstrate how to design an effective DNN model for detailed scheduling and operational planning of a complex flowshop. This method is open to additional complexity, modification of objective functions, and customized KPIs. One future possibility is to include preventive maintenance and sudden breakdowns as new input parameters of the system. These input parameters act as a new KPI and will lead to the generation of the OPSs to meet the KPIs while generating Zero Breakdown processes. Another line of research could be to compare the proposed technique with evolutionary optimization methods such as [43], [44].

TABLE 11. Applied test Dataset for validation.

Scenario	Furnace 1		Furnace 2		Dry Machine		Press 1		Press 2		Green Machine		Sintering 1		Sintering 2		Finishing Machine		Total Cost (€)		End of Process time (hrs)		
	EC(Kwh)	EC(Kwh)	EC(Kwh)	EC(Kwh)	EC(Kwh)	EC(Kwh)	EC(Kwh)	EC(Kwh)	EC(Kwh)	EC(Kwh)	EC(Kwh)	EC(Kwh)	EC(Kwh)	EC(Kwh)	EC(Kwh)	EC(Kwh)	EC(Kwh)	EC(Kwh)	EC(Kwh)	Cost (€)	Cost (€)	Cost (€)	Cost (€)
2	2100	2440	640	132	0	325	325	335	265	540	880	982	492.5	1062	650	840	2314.7	7661.2	840	840	2314.7	7661.2	180.25
3	2100	2540	640	102.5	22.5	325	289.5	324.3	245.52	6589.32	531	1062	1223	531	1062	1023	531	832	2186.27	8982.77	832	832	184
4	2100	2640	640	96.39	0	322	302	250	220.8	6571.19	561	1122	1022	492.28	1062	1052	640	561	2013	7463.28	561	561	178
30	2100	1440	640	70	35	290	212.5	362.5	230	5380	944	944	944	944	472	472	472	944	1944	8080	944	944	158.25
49	2100	1440	640	112.5	0	310	237.5	375	245	5460	982	491	982	492.5	982	982	491	982	1982	8366.5	491	982	176.5
55	2100	1440	480	112.5	0	310	250	362.5	245	5300	491	491	491	491	982	982	491	982	1982	7875.5	491	982	178
88	2100	2640	640	122.5	0	335	212.5	412.5	250	6712.5	513	1026	513	1026	1026	1026	513	1026	1982	9182	513	1026	178
95	2100	2640	640	122.5	0	335	237.5	387.5	250	6712.5	502	502	502	502	502	502	502	704	1902	6422	502	704	178
99	2100	2640	640	122.5	0	335	225	400	250	6712.5	513	1026	513	1026	1026	513	1026	2513	8669	513	1026	178	
103	2100	1440	640	57.5	52.5	320	200	375	230	5415	1060	530	1060	1060	530	1060	530	2060	8421	530	2060	180	
108	2100	1440	640	110	0	320	250	325	230	5415	513	1026	513	1026	1026	513	1026	2513	8669	513	1026	178	
114	2100	1440	640	110	0	320	237.5	337.5	230	5415	487	487	487	487	974	974	487	974	1974	7818	487	974	159
125	2100	2640	640	82.5	27.5	320	200	375	230	5355	480	980	980	980	980	980	480	980	1480	7374	480	980	160
142	2800	2640	800	107.5	40	340	187.5	425	245	6717.5	1062	531	1062	531	1062	531	531	531	2062	8438.5	531	531	181
149	2800	2640	800	147.5	0	350	262.5	400	265	7665	551	1102	551	1102	551	1102	551	1102	2062	7412	551	1102	183.5
187	2800	2640	640	127.5	15	375	250	462.5	285	7595	754	856	527	527	1054	527	527	2054	7553	527	527	182	
189	2100	2640	640	142.5	0	375	300	412.5	285	7595	854	527	954	527	1054	527	527	2054	7553	527	527	182	
193	2800	2640	800	87.5	57.5	375	312.5	400	285	7055	1114	104	557	557	1114	1114	104	1054	2527	8778	104	1054	180
204	2100	2640	800	85	57.5	375	300	412.5	285	7755	561	561	561	561	1125	1125	561	561	2557	8231	561	561	184.5
215	2100	2640	800	122.5	0	335	212.5	410	249	6549	513	1026	513	1026	1026	513	1026	2513	8669	513	1026	178	
219	2100	1440	640	57.5	54.5	335	237.5	375	245	5484.5	1074	532	745	1043	538	1060	830	830	2060	8712	532	745	182.5
226	2100	1440	640	123	0	330	335	325	230	5443	513	1026	513	1026	1026	513	1026	2513	8669	513	1026	178	
246	2100	1440	640	110	0	320	212.5	337.5	230	5380	487	487	487	487	974	974	487	974	1974	7818	487	974	159
249	2100	2640	640	82.5	27.5	320	237.5	324	224.6	5396.1	480	980	980	980	980	980	480	980	1480	7507	480	980	160
264	2800	2640	800	109.5	20	320	200	450	260	6751.3	1083	533	745	1065	531	1102	531	1102	2062	8244.5	533	745	185
275	2800	2640	640	147.5	0	340	250	400	280	7595.5	802	762	562	562	1062	531	1102	531	1102	7714	531	1102	183.5
289	2800	2640	640	127.5	15	350	237.5	462.5	280	7552.5	742	856	527	527	1053	527	527	2054	7669	527	527	182	
297	2800	2640	480	145	0	375	200	417.5	247	7304.5	850	529	1064	834	596	1084	1054	524	2227	8762	834	596	184

APPENDIX I

A sample scenario in Arena simulation package for operational planning and scheduling of the machines in the production line.

See Table 8.

- [18] S. S. Kulkarni and R. Sridharan, "A hybrid neural network- meta heuristics approach for permutation flow shop scheduling problems," in *Proc. IEEE Int. Conf. Ind. Eng. Manage.*, Dec. 2010, pp. 286–290.
- [19] X. Li, H. Tang, Z. Yang, R. Wu, and Y. Luo, "Integrated optimization approach of hybrid flow-shop scheduling based on process set," *IEEE Access*, vol. 8, pp. 223782–223796, 2020.
- [20] Y. Zhou, J. J. Yang, and L. Y. Zheng, "Multi-agent based hyper-heuristics for multi-objective flexible job shop scheduling: A case study in an aero-engine blade manufacturing plant," *IEEE Access*, vol. 7, pp. 21147–21176, 2019.
- [21] Y. Zhou, J.-J. Yang, and L.-Y. Zheng, "Hyper-heuristic coevolution of machine assignment and job sequencing rules for multi-objective dynamic flexible job shop scheduling," *IEEE Access*, vol. 7, pp. 68–88, 2018.
- [22] F. B. Oyebolu, R. Allmendinger, S. S. Farid, and J. Branke, "Dynamic scheduling of multi-product continuous biopharmaceutical facilities: A hyper-heuristic framework," *Comput. Chem. Eng.*, vol. 125, pp. 71–88, Jun. 2019.
- [23] S. Zhou, X. Li, N. Du, Y. Pang, and H. Chen, "A multi-objective differential evolution algorithm for parallel batch processing machine scheduling considering electricity consumption cost," *Comput. Oper. Res.*, vol. 96, pp. 55–68, Aug. 2018.
- [24] R. S. M. Omar, U. Venkatadri, C. Diallo, and S. Mrishih, "A data-driven approach to multi-product production network planning," *Int. J. Prod. Res.*, vol. 55, no. 23, pp. 7110–7134, Dec. 2017.
- [25] X. Yao, J. Zhang, Y. Li, and C. Zhang, "Towards flexible RFID event-driven integrated manufacturing for make-to-order production," *Int. J. Comput. Integr. Manuf.*, vol. 31, no. 3, pp. 228–242, Mar. 2018.
- [26] P. Goodall, R. Sharpe, and A. West, "A data-driven simulation to support remanufacturing operations," *Comput. Ind.*, vol. 105, pp. 48–60, Feb. 2019.
- [27] D. A. Rossit, F. Tohmé, and M. Frutos, "A data-driven scheduling approach to smart manufacturing," *J. Ind. Inf. Integr.*, vol. 15, pp. 69–79, Sep. 2019.
- [28] C. Qian, Y. Zhang, C. Jiang, S. Pan, and Y. Rong, "A real-time data-driven collaborative mechanism in fixed-position assembly systems for smart manufacturing," *Robot. Comput. Integr. Manuf.*, vol. 61, Feb. 2020, Art. no. 101841.
- [29] W. Li, G. G. Wang, and A. H. Gandomi, "A survey of learning-based intelligent optimization algorithms," *Arch. Comput. Methods Eng.*, vol. 28, pp. 1–19, Feb. 2021.
- [30] S. Abdullah and M. Abdolrazzagah-Nezhad, "Fuzzy job-shop scheduling problems: A review," *Inf. Sci.*, vol. 278, pp. 380–407, Sep. 2014.
- [31] P. Priore, A. Gómez, R. Pino, and R. Rosillo, "Dynamic scheduling of manufacturing systems using machine learning: An updated review," *AI EDAM*, vol. 28, no. 1, pp. 83–97, Feb. 2014.
- [32] B. Çaliş and S. Bulkan, "A research survey: Review of AI solution strategies of job shop scheduling problem," *J. Intell. Manuf.*, vol. 26, no. 5, pp. 961–973, Oct. 2015.
- [33] J. P. U. Cadavid, S. Lamouri, B. Grabot, R. Pellerin, and A. Fortin, "Machine learning applied in production planning and control: A state-of-the-art in the era of industry 4.0," *J. Intell. Manuf.*, vol. 31, pp. 1–28, Jan. 2020.
- [34] J. Shahrabadi, M. A. Adibi, and M. Mahootchi, "A reinforcement learning approach to parameter estimation in dynamic job shop scheduling," *Comput. Ind. Eng.*, vol. 110, pp. 75–82, Aug. 2017.
- [35] G. Metan, I. Sabuncuoglu, and H. Pierreval, "Real time selection of scheduling rules and knowledge extraction via dynamically controlled data mining," *Int. J. Prod. Res.*, vol. 48, no. 23, pp. 6909–6938, Dec. 2010.
- [36] A. Shahzad and N. Mebarki, "Learning dispatching rules for scheduling: A synergistic view comprising decision trees, Tabu search and simulation," *Computers*, vol. 5, no. 1, p. 3, Feb. 2016.
- [37] P. Priore, R. Pino, J. Parreño, J. Puente, and B. Ponte, "Real-time scheduling of flexible manufacturing systems using support vector machines and case-based reasoning," *J. Econ., Bus. Manage.*, vol. 3, no. 1, pp. 54–59, 2015.
- [38] R.-S. Guh, Y.-R. Shiu, and T.-Y. Tseng, "The study of real time scheduling by an intelligent multi-controller approach," *Int. J. Prod. Res.*, vol. 49, no. 10, pp. 2977–2997, May 2011.
- [39] J. N. Gupta, A. Majumder, and D. Laha, "Flowshop scheduling with artificial neural networks," *J. Oper. Res. Soc.*, vol. 71, no. 10, pp. 1–19, 2019.
- [40] H. Kim, D.-E. Lim, and S. Lee, "Deep learning-based dynamic scheduling for semiconductor manufacturing with high uncertainty of automated material handling system capability," *IEEE Trans. Semicond. Manuf.*, vol. 33, no. 1, pp. 13–22, Feb. 2020.
- [41] A. Noorul Haq, T. R. Ramanan, K. S. Shashikant, and R. Sridharan, "A hybrid neural network-genetic algorithm approach for permutation flow shop scheduling," *Int. J. Prod. Res.*, vol. 48, no. 14, pp. 4217–4231, 2010.
- [42] P. Korytkowski, T. Wiśniewski, and S. Rymaszewski, "An evolutionary simulation-based optimization approach for dispatching scheduling," *Simul. Model. Pract. Theory*, vol. 35, pp. 69–85, Jun. 2013.
- [43] G.-G. Wang, S. Deb, and Z. Cui, "Monarch butterfly optimization," *Neural Comput. Appl.*, vol. 31, no. 7, pp. 1995–2014, 2019.
- [44] J. Li, H. Lei, A. H. Alavi, and G.-G. Wang, "Elephant herding optimization: Variants, hybrids, and applications," *Mathematics*, vol. 8, no. 9, p. 1415, Aug. 2020.
- [45] M. U. Akhtar, M. H. Raza, and M. Shafiq, "Role of batch size in scheduling optimization of flexible manufacturing system using genetic algorithm," *J. Ind. Eng. Int.*, vol. 15, no. 1, pp. 135–146, Mar. 2019.
- [46] X. Feng and Z. Xu, "Integrated production and transportation scheduling on parallel batch-processing machines," *IEEE Access*, vol. 7, pp. 148393–148400, 2019.
- [47] A. Negahban and J. S. Smith, "Simulation for manufacturing system design and operation: Literature review and analysis," *J. Manuf. Syst.*, vol. 33, no. 2, pp. 241–261, 2014.
- [48] D. Li, M. Li, X. Meng, and Y. Tian, "A hyperheuristic approach for intercell scheduling with single processing machines and batch processing machines," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 45, no. 2, pp. 315–325, Feb. 2014.
- [49] O. Ozturk, M. A. Begen, and G. S. Zaric, "A branch and bound algorithm for scheduling unit size jobs on parallel batching machines to minimize makespan," *Int. J. Prod. Res.*, vol. 55, no. 6, pp. 1815–1831, Nov. 2017.
- [50] E. Huang and K. Wu, "Job scheduling at cascading machines," *IEEE Trans. Autom. Sci. Eng.*, vol. 14, no. 4, pp. 1634–1642, Oct. 2017.
- [51] W. Li, B. R. Nault, and H. Ye, "Trade-off balancing in scheduling for flow shop production and perioperative processes," *Eur. J. Oper. Res.*, vol. 273, no. 3, pp. 817–830, Mar. 2019.
- [52] Y. Tan, L. Mönch, and J. W. Fowler, "A hybrid scheduling approach for a two-stage flexible flow shop with batch processing machines," *J. Scheduling*, vol. 21, no. 2, pp. 209–226, Apr. 2018.
- [53] M. Abedi, H. Seidgar, H. Fazlollahabadi, and R. Bijani, "Bi-objective optimisation for scheduling the identical parallel batch-processing machines with arbitrary job sizes, unequal job release times and capacity limits," *Int. J. Prod. Res.*, vol. 53, no. 6, pp. 1680–1711, Mar. 2015.
- [54] J. Lee, H. Jang, and H. Kim, "Iterative job splitting algorithms for parallel machine scheduling with job splitting and setup resource constraints," *J. Oper. Res. Soc.*, vol. 72, no. 4, pp. 1–20, 2020.
- [55] D. Shi, W. Fan, Y. Xiao, T. Lin, and C. Xing, "Intelligent scheduling of discrete automated production line via deep reinforcement learning," *Int. J. Prod. Res.*, vol. 58, no. 11, pp. 3362–3380, Jun. 2020.
- [56] A. Al-Shayea, E. Fararah, E. A. Nasr, and H. A. Mahmoud, "Model for integrating production scheduling and maintenance planning of flow shop production system," *IEEE Access*, vol. 8, pp. 208826–208835, 2020.
- [57] Y. Fu, H. Wang, G. Tian, Z. Li, and H. Hu, "Two-agent stochastic flow shop deteriorating scheduling via a hybrid multi-objective evolutionary algorithm," *J. Intell. Manuf.*, vol. 30, no. 5, pp. 2257–2272, Jun. 2019.
- [58] S. M. Jeon and G. Kim, "A survey of simulation modeling techniques in production planning and control (PPC)," *Prod. Planning Control*, vol. 27, no. 5, pp. 360–377, Apr. 2016.
- [59] A. Mousavi and H. R. A. Siervo, "Automatic translation of plant data into management performance metrics: A case for real-time and predictive production control," *Int. J. Prod. Res.*, vol. 55, no. 17, pp. 4862–4877, Sep. 2017.
- [60] A. Barroy, "Enable predictive production control in manufacturing systems and assess optimum schedules with discrete-event simulation models," M.Sc. thesis, Tech. Rep., Brunel University London, Uxbridge, U.K., Sep. 2018.
- [61] W. D. Kelton, R. P. Sadowski, and N. B. Zupick, *Simulation With Arena*. New York, NY, USA: McGraw-Hill, 1998.
- [62] M. Rocha, P. Cortez, and J. Neves, "Evolution of neural networks for classification and regression," *Neurocomputing*, vol. 70, nos. 16–18, pp. 2809–2816, Oct. 2007.
- [63] S. Wandelt, X. Sun, E. Menasalvas, A. Rodríguez-González, and M. Zanin, "On the use of random graphs as null model of large connected networks," *Chaos, Solitons Fractals*, vol. 119, pp. 318–325, Feb. 2019.
- [64] S. Langer, "Analysis of the rate of convergence of fully connected deep neural network regression estimates with smooth activation function," *J. Multivariate Anal.*, vol. 182, Mar. 2021, Art. no. 104695.

- [65] Z. Zhu, K. Ferreira, N. Anwer, L. Mathieu, K. Guo, and L. Qiao, "Convolutional neural network for geometric deviation prediction in additive manufacturing," *Proc. CIRP*, vol. 91, pp. 534–539, Aug. 2020.
- [66] Q. Cheng, H. Li, Q. Wu, L. Ma, and K. N. Ngan, "Parametric deformable exponential linear units for deep neural networks," *Neural Netw.*, vol. 125, pp. 281–289, May 2020.
- [67] C. D. Alecsa, T. Pința, and I. Boros, "New optimization algorithms for neural network training using operator splitting techniques," *Neural Netw.*, vol. 126, pp. 178–190, Jun. 2020.
- [68] Q. Xu, M. Zhang, Z. Gu, and G. Pan, "Overfitting remedy by sparsifying regularization on fully-connected layers of CNNs," *Neurocomputing*, vol. 328, pp. 69–74, Feb. 2019.
- [69] N. Settouti, M. E. A. Bechar, and M. A. Chikh, "Statistical comparisons of the top 10 algorithms in data mining for classification task," *Int. J. Interact. Multimedia Artif. Intell., Special Issue Artif. Intell. Underpinning*, vol. 4, pp. 46–51, Sep. 2016.



MORAD DANISHVAR received the B.Sc. degree in electronic engineering, the M.Sc. degree in engineering management, and the Ph.D. degree from Brunel University London, U.K., in 2015. He is currently a Senior Research Fellow and the Co-Director of the Centre for Digital Manufacturing, College of Engineering, Design and Physical Sciences, Brunel University London. From 2017 to 2020, he has worked on the EU Horizon 2020 Z-Factor Project, which focuses on zero defects in manufacturing systems. His research interests include data analytics, machine learning, AI, and smartification of industrial systems. He is a Senior Research Fellow on the EU Horizon 2020 DEEP PURPLE.



SEBELAN DANISHVAR received the Ph.D. degree in biomedical engineering from Tarbiat Modares University, Tehran, Iran, in 2007.

He was on an Academic Board at the Sahand University of Technology and the University of Tabriz, from 2008 to 2018. He is currently a Senior Researcher with the Department of Computer Science, College of Engineering, Design and Physical Sciences, Brunel University London, U.K. His current research interests include machine learning, signal and image processing, and analysis.



EVINA KATSOU is currently a Professor at the College of Engineering, Design and Physical Sciences, Brunel University London. Her research has developed a new dimension in deployment of advanced data analytics methods, such as multivariate statistics, clustering techniques for dimensionality reduction, linear and non-linear supervised learning techniques, artificial neural networks, support vector machines, and simplified mechanistic equations to identify and reconstruct complex relationships between observed and latent process variables. The models being developed in her research are leading to the accurate measurement of GHGs emissions of treatment processes and being adopted as an indicator of measuring environmental impact in a number of industrial applications, such as water systems, process industry, and manufacturing.



S. AFSHIN MANSOURI received the B.Sc., M.Sc., and Ph.D. degrees in industrial engineering from the Amirkabir University of Technology. He is currently a Professor of operations and supply chain management at the Brunel Business School, Brunel University London. He is a pioneer in the area of green scheduling and working to extend new applications of this concept in maritime and manufacturing sectors. His research interests include sustainable operations management, humanitarian operations and disaster management, green scheduling, data-driven decision making, and business analytics. He is a fellow of the Higher Education Academy and a member of INFORMS.



ALIREZA MOUSAVI (Senior Member, IEEE) received the B.Sc. degree in industrial engineering and the Ph.D. degree in system engineering from Brunel University London.

He is currently a Reader at the College of Engineering, Design and Physical Sciences, Brunel University London. His research interests include digital transformation and smartification of industrial systems, especially within the industry 4.0 context covering sensors-actuation, signal processing and feature extraction, machine learning, modeling, control, and optimization.

• • •