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Development of an Efficient Prediction Model for Optimal Design of Serial Production Lines

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ABSTRACT One of the problems encountered in the design and implementation of a serial production line (SPL) is the buffer size between the machine tools. The buffer size of the SPL has an important impact on the productivity of the whole production system. The machine tools' characteristics including their uptimes and downtimes and the process parameters are the main factors that affect the decision regarding the buffer size, and thus the productivity of the SPL. Due to the dynamic nature of this problem, it is complex to find the optimal buffer size in SPL. Thus, in this paper, an Efficient Prediction Model (EPM) is developed using Artificial Neural Network (ANN). The purpose of the developed EPM is to find the buffer size between each succeeding pair of machine tools in SPL at any given uptimes and downtimes of machine tools. An optimization model based on genetic algorithms (GA) is used to generate the learning data for the prediction model to find the optimal or near optimal buffer size of the bay of each machine tool in SPL. The proposed approach integrates the optimization and prediction methodologies to evaluate, and predict the optimal buffer sizes for maximum productivity. Including uptime and downtime parameters enable the proposed method to be used to improve the design of running SPL as well as to design a new SPL. Numerical examples for five and fifteen machine tools were conducted independently in this research and the results show the ability of the proposed method to determine the optimal buffer sizes in a reasonable amount of time. In particular, the results of case studies show that the developed model accurately predict the optimal buffer size, especially for the case of five machines and even for a higher number of machine tools yet with acceptable but less accuracy. Finally, the performance of the proposed approach was compared with some results of the state of the art methods reported in the literature. The comparison shows the superiority of the present approach to identify buffer sizes for higher throughput under the same uptimes and downtimes.

INDEX TERMS Flexible manufacturing system; serial production line; optimization; prediction model; buffer size; productivity

NOTATION

Abbreviations	Descriptions
N	Number of buffers in the main production line
B_i	Buffer size in front of the machine tool i+1
F(i)	Fitness of individual i
P_size	Population size (number of individuals in population)
S	Number of individuals selected by applying elitist strategy
IND(i)	Individual i
POP(i)	Population i
CP	Crossover point
Cr	Crossover rate
Mr	Mutation rate
p_i	uptime parameters of machine i
r_i	downtime parameters of machine i

I. INTRODUCTION

A serial production flow/transfer line is a system in which machine tools are placed in series with buffers of in-process parts between them [1]. Serial production line (SPL) is a common form of mass production systems in modern plants. In order to design an efficient production system, the size of buffers in the bay of machine tools in SPL should be optimized. The main purpose for maintaining buffers in the production line is to carry out a series of operations more independently [2]. Increasing the independence of operations reduces the effect of interruption triggered by events such as machine failure. Furthermore, it absorbs the production variability caused by stochasticity of machine tools and/or due to differences in their capacity, processing time or throughput of different stages in the production line. However, the addition of buffers results in extra capital investment, space, and inventory [3]. Therefore, it is vital to choose buffer sizes efficiently. In production systems, the uptimes and downtimes parameters of the machine tool has an important impact on the buffer size on the bay of each machine tools in SPL. The machine tool uptime refers to the amount of time that the machine tool is working and available, while downtime refers to the amount of time that the machine tool is not operating or unavailable. Changing the uptimes and downtimes parameters affects the production rate (throughput) of the production system. The flexibility and production rate of the production system can be improved with a well-optimized production line [4]. Therefore, identifying the optimal buffer size has been a serious challenge in manufacturing industries, and there is a need for an effective and efficient methodology that can determine optimal buffer sizes at different levels of uptimes and downtimes parameters of the machine tools of the production system. Moreover, this determination of buffer size needs to be reached in a relatively short time. In this work, it is assumed that the machine tools and manufacturing processes have already been selected and the uptimes and downtimes parameters of all machine tools are well defined. Thus, the only decision variable is to optimize the buffer size at these uptimes and downtimes to improve the production rate of the system.

As previously emphasized, the selection of suitable buffer sizes for any production line has been a critical task because it greatly affects the throughput of the system. In this context, a significant amount of research has been carried out to address the buffer size problem. For example, Bulgak and Sanders [5], implemented simulated annealing (SA) technique to determine optimal buffer sizes for a system comprising both automated inspection as well as assembly lines. Bulgak [6], also optimized the allocation of inter-stage buffers to optimize the overall production rate of the system. In particular, a simulation model based on ANN and GA had been proposed to deal with the optimization of buffer allocation in split-and-merge assembly systems. Similarly, a group of researchers developed a meta-heuristic approach based on Tabu search algorithm to determine buffer location and sizes for a given manufacturing line [7]. Furthermore, Tsadiras et al. [8], presented the prediction capabilities of ANN in production systems and explained how they can be trained to obtain better and quick results. Nahas et al. [9], utilized a GA algorithm to maximize the production rate by simultaneously selecting buffers and machines in assembly/disassembly manufacturing networks. They reported that efficient machines and large buffers elevate the average production rate of the system; however, this requires huge financial investment. Therefore, they formulated a design model based on combinatorial optimization for assembly/disassembly networks and used buffers and machines as decision variables in the problem. Moreover, Papadopoulos and Vidalis [10], proposed a heuristic algorithm to deal with the buffer allocation problem in unreliable and/or unbalanced production lines. For production systems including a supporting line, researchers utilized GA to develop a decision support system deciding buffer size for a flexible transfer line with bypass lines [11]. In addition, Qudeiri et al. [12], used genetic algorithms to optimize the buffer size and workstation capacity of serial parallel production lines. The results were presented in which a flexible production system with sub-lines was modeled and they included the buffer size in the model as well [13]. Hasama et al. [14], used the dynamic programming approach to optimize the buffer size allocation for an assembly line. A numerical approach has been applied to design the buffer in an automated transfer line to alleviate the effect of breakdown on the line efficiency [15]. Several studies utilized simulation techniques to deal with SPL optimization problem [16-18].

Buffer sizes in asynchronous assembly system were studied using a combination of ANN and simulated annealing [19]. The buffer allocation problem has also been investigated for optimal solutions by applying artificial intelligence (AI), GA, and ANN [2]. Zandieh et al. [20], presented an integrated simulation and meta-heuristic algorithm method to study the buffer allocation problem. Furthermore, Han and Park [21] presented an analytical method to optimize buffer allocation for maximum throughput in a serial production line involving workstations, buffers, and quality inspection machines. However, it was found time consuming especially when the system becomes complex. Similarly, Usubamatov et al. [22], proposed an analytical approach to compute the productivity of an automated line comprising both parallel and serial machines with buffer storages.

Shao et al. [23], proposed a novel method for solving line balancing and buffer allocation problems at the same time. Production rate was calculated using a simulation procedure. In particular, non-dominated Sorting Genetic Algorithm-II (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO) were applied to a real case study, and total cost for machine tools and buffer capacity were optimized. Results reported good efficacy of the proposed method. Kang and Ju [24], studied SPL from preventive maintenance perspective and with finite buffer size. In this research study, Markov decision models were utilized to

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obtain optimal maintenance policy with a single buffer system between two machines. The model effectiveness was shown with the help of numerical examples. Ouzineb et al. [25], investigated the problem of buffer size and inspection station locations in unreliable production lines. The aim was to optimize the buffer size, number and location of inspection stations, fulfilling customer demand with minimal total cost. An exact mathematical method was presented to solve this complex problem. It was reported that the developed method was capable to solve the problem instances with up to 30 machines tools, which was previously not solved. Dolgui et al. [26], studied a multicriterial optimization problem for volumes of buffers in a production line. Evolutionary algorithms namely SIBEA (Simple Indicator-Based Evolutionary Algorithm), and SEMO (Simple Evolutionary Multi-objective Optimizer) were implemented to solve the problem. Results showed that problems with larger dimension were solved efficiently by the proposed method.

In another research study, simulation based optimization approach was utilized for optimization of buffer level, and processing time simultaneously [27]. A real world problem was modeled using simulation, and then design of experiments were used for obtaining the mathematical model of this bi-objective problem. The mathematical model was optimized using multi-objective GA. Liberopoulos [28] investigated a production line that operates on Echelon buffer policy. They modeled the system as a queuing network, and further divided each segment into sub-systems with 2 machines and their buffer. Each sub-system was solved using Markov chain. Results showed that the developed method provided accurate results. Xi et al. [29] presented a multi-objective optimization problem for a unbalanced series-parallel production lines. The objective was to optimize machine types, number of parallel machines, and buffer capacities for obtaining desired throughput rate and cycle time. The developed method was based on decomposing and coordination, in which a large production line was decomposed into several small lines, and small lines were optimized separately, then through coordination process a unified result was obtained. The developed method was compared against SA and NSGA-II, and the results showed better efficiency of the developed method.

Weiss et al. [30] conducted a comprehensive literature review on the buffer allocation problem in production lines. The review highlighted the future research directions in this field. Kose and Kilincci [31] investigated the problem of buffer allocation in open serial production lines. The investigation considered two conflicting objectives, maximizing the average system production rate and minimizing total buffer size. Elitist NSGA-II, and a special version of a multi-objective SA were utilized to optimize the stated objectives. Discrete event simulation was employed to estimate the performance measures for the production systems. The results revealed that the developed methodology had a substantial potential to minimize the total buffer space. Koyuncuoğlu and Leyla [32], presented a comparative study for solving the buffer allocation problem. Two algorithms under consideration were combat GA and Big Bang-Big Crunch algorithm. The objective was to maximize the throughput of the line under the total buffer size constraint for unreliable production lines. The results concluded that the Big Bang-Big Crunch algorithm provided better results than combat GA. Demir and Koyuncuoğlu [33] proposed a variable neighborhood search approach for the buffer allocation problem in a serial production line. The proposed VNS-based solution approach was found highly effective in finding good-quality solutions, according to the results reported.

The previous studies attempted to optimize the buffer size in a relatively long processing time. Moreover, none of the aforementioned studies solved this problem through the integration of optimization and prediction based on the uptimes and downtimes parameters as proposed in this work. In this context, this methodology aims to optimize buffer size, thereby maximizing the throughput of the given SPL under specified assumptions and constraints including the uptimes and downtimes of the machine tools in SPL. The proposed approach can solve the problem in a relatively short time to enable the management to take quick decisions regarding the selection of buffer sizes in the production line. Thus, the proposed method will enable generation of new sets of buffer sizes that achieve the maximum productivity in relatively short time. In addition to the serial production line, the proposed method can be applied to complex production lines such as production lines with rework path and hybrid serial-parallel production systems, etc. Following this introduction, the remainder of the paper is organized as follows. Section II present the model of the serial production line. The resolution approach for optimal SPL is discussed in Section III. Section IV presents numerical verification results. The paper is concluded in section V.

II. MODEL OF THE SERIAL PRODUCTION LINE

The structure of SPL studied in this paper is shown in Figure 1.

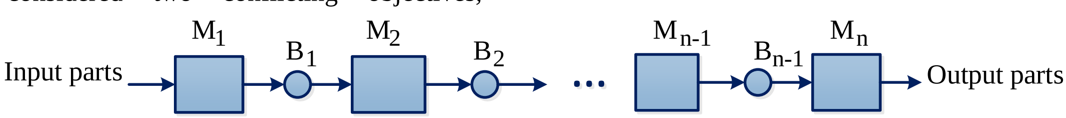

FIGURE 1. Structure of SPL containing n machine tools through which the parts are processed in series.

The main assumptions pertaining the SPL components are given below,

1. The SPL consists of n machine tools (M_1, M_2, …., M_n) and n-1 buffers (B_1, B_2, …., B_{n-1}). The machine tools are arranged serially and each buffer separating each consecutive pair of machine tools.
2. Each machine tool M_i, $i = 1, 2, \ldots, n$, has two states: up and down. When up, the machine is capable of producing with the rate 1 part per unit of time (cycle); when the machine is down, no production takes place.
3. The uptime and the downtime of each machine M_i, $i = 1, 2, \ldots, n$, are random variables distributed exponentially with parameters p_i and r_i, respectively. Please note that $1/p_i$ and $1/r_i$ are the uptime values of machine i.
4. Each buffer B_i, $i = 1, 2, \ldots, n$, is characterized by its capacity, $0 \leq N_i < \infty$.
5. Machine tool M_i is starved at time t if buffer B_{i-1} is empty at time t. The first machine tool in SPL, M_1 is never starved.
6. Machine tool M_i is blocked at time t if B_i is full at time t. The last machine tool in SPL, M_n is never blocked.

A. THROUGHPUT EVALUATION OF SPL

Recently, the design, implementation, and parameter identification and optimization of SPL have been reported in a number of research studies such as [34-38]. Among others, Sun et al. [36] studied production lines characterized by the Bernoulli serial line model and developed algorithms to identify model parameters to fit the system throughput. Furthermore, Yan et al. [38] proposed an improved aggregation method to improve the prediction accuracy of traditional aggregation method for the Bernoulli serial production lines with unreliable machines and finite buffers. There are many approximation approaches used to evaluate the SPL based on aggregation and decomposition. This paper follows the aggregation procedure presented in [39] to evaluate the SPL at given uptimes and downtimes parameters and buffer sizes for all machine tools in the SPL. This aggregation procedure is described below. Consider the serial production line with M machines shown in Figure 1 defined by assumptions 1 to 6.

The first two machine tools (M_1 and M_2) are aggregated into a single machine, M_2^f, with the following uptime and downtime parameters:

$$p_2^f = p_2 + r_2 Q(p_1, r_1, p_2, r_2, N_1) \qquad (1)$$

$$r_2^f = r_2 - r_2 Q(p_1, r_1, p_2, r_2, N_1) \qquad (2)$$

where $Q(p_1, r_1, p_2, r_2, N_1)$ is the probability that the machine tool M_2 is starved and is defined as given in Eq. (3) follows [39]:

$$Q(p_a, r_a, p_b, r_b, N) = \begin{cases} \frac{(1-e_a)(1-\emptyset)}{1-\emptyset e^{-\beta N}}, & if\ \frac{p_a}{r_a} \neq \frac{p_b}{r_b} \\ \frac{p_a(p_a+p_b)(r_a+r_b)}{(p_a+r_a)[(p_a+p_b)(r_a+r_b)+p_b r_a(p_a+p_b+r_a+r_b)N]}, & if\ \frac{p_a}{r_a} = \frac{p_b}{r_b} \end{cases} \qquad (3)$$

and

$$e_i = \frac{r_i}{p_i + r_i}, i = a, b,$$

$$\emptyset = \frac{e_a(1-e_b)}{e_b(1-e_a)}, \qquad (4)$$

$$\beta = \frac{e_a(p_a + p_b + r_a + r_b)(p_a r_b - p_b r_a)}{(p_a + p_b)(r_a + r_b)}$$

Next, aggregation in forward direction (forward aggregation); the resulted equivalent machine tool, M_2^f defined by p_2^f and r_2^f is aggregated with M3 to result in M_3^f defined by p_3^f and r_3^f, with the parameters defined as above, and so on until all n machine tools are aggregated in a single one, M_n^f defined by p_n^f and r_n^f. Then, in the backward aggregation, the last machine, Mn, is aggregated with M_{n-1}^f to result in M_{n-1}^b defined by p_{n-1}^b and r_{n-1}^b and so on until all machine tools are again aggregated in a single machine, M_1^b defined by p_1^b and r_1^b. The procedure is repeated until the following criteria is satisfied:

$$\frac{r_n^f}{p_n^f} = \frac{r_1^b}{p_1^b} \qquad (5)$$

Formally, this process is represented as follows:

$$r_i^f(s+1) = r_i - r_i Q\big(p_{i-1}^f(s+1), r_{i-1}^f(s+1), p_i^b(s+1), r_i^b(s+1), N_{i-1}\big), i = 2, \ldots, n$$

$$\begin{aligned} p_i^f(s+1) &= p_i + r_i Q\big(p_{i-1}^f(s+1), r_{i-1}^f(s+1), p_i^b(s+1), r_i^b(s+1), N_{i-1}\big), i = 2, \dots, n \\ r_i^b(s+1) &= r_i - r_i Q\big(p_{i+1}^b(s+1), r_{i+1}^b(s+1), p_i^f(s), r_i^f(s), N_i\big), i = 1, \dots, n-1 \\ p_i^b(s+1) &= p_i + r_i Q\big(p_{i+1}^b(s+1), r_{i+1}^b(s+1), p_i^f(s), r_i^f(s), N_i\big), i = 1, \dots, n-1 \end{aligned} \quad (6)$$

with the following initial conditions:

$$p_i^f(0) = p_i, \quad r_i^f(0) = r_i, \qquad \forall\, i = 2, \dots, n-1,$$

and boundary conditions:

$$\begin{aligned} p_1^f(s) &= p_1, & r_1^f(s) &= r_1, \\ p_n^b(s) &= p_n, & r_n^b(s) &= r_n, \end{aligned}$$
$$\forall\, s = 0, 1, 2, \dots$$

where function $Q(p_a, r_a, p_b, r_b, N)$ is defined in Eq. (3).

Finally, production rate for the defined SPL can be approximated as follows:

$$PR(p_1, r_1, \dots, p_n, r_n, N_1, \dots, N_{n-1}) = \frac{r_n^f}{p_n^f + r_n^f} = \frac{r_1^b}{p_1^b + r_1^b}. \quad (7)$$

This aggregation procedure is described in the appendix. The SPL evolution procedure can be summarize graphically as shown in Figure 2.

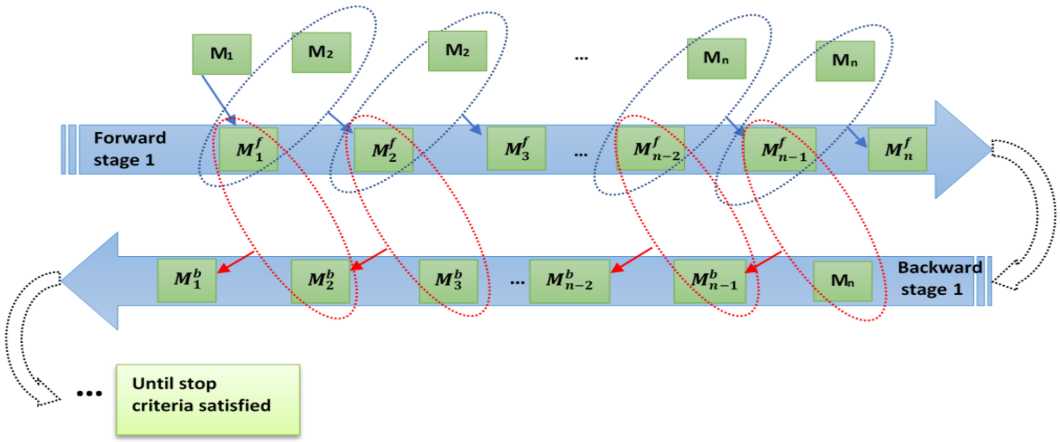

FIGURE 2. **SPL evaluation procedure.**

III. RESOLUTION APPROCH FOR OPTIMAL SPL

To find the optimal design for SPL, this study utilizes GA to develop an optimization model, the fitness function for GA used the evaluation method for SPL discussed in section 2. The proposed optimization model identifies the buffer size that achieve the highest production rate at any given uptime (p_i) and the downtime (r_i) parameters. Then, and based on the optimization module this study develops a prediction module to predict the buffer size of the SPL for any given pi and r_i $\forall$ i=1,…, n-1, where n is the number of machine tools in the SPL. The proposed prediction model can reduce the computational time for the determination of buffer sizes at a given pi and r_i. The optimization module can be used again in this stage to validate that the predicted buffer sizes leads to the highest production rate.

A. OTIMIZATION MODEL

In this research, GA is utilized to obtain the optimal or near optimal buffer size. GA is one of the well-known meta-heuristic optimization methods, which finds the optimal or near optimal solution based on natural selection and genetics principles. GA begins with an initial population including arbitrarily selected solutions known as individuals, where each individual is defined by a group of variables known as Genes. Then determining the fitness of all individuals in the initial population. This is followed by the selection of the fittest individuals allows them to pass their genes to the next generation. These iterations are repeated to obtain the optimal or near optimal result of the problem. The solution of the highest fitness becomes the candidate solution to the given problem. Figure 3 shows the outline of GA.

The first step to implement the GA approach is to define the structure of an individual and encode the individual's elements. In this research, the individual is defined as a set with *n-1* elements, where n is the number of machine tools in SPL. Each of these elements represents one buffer. The individual is defined as follows.

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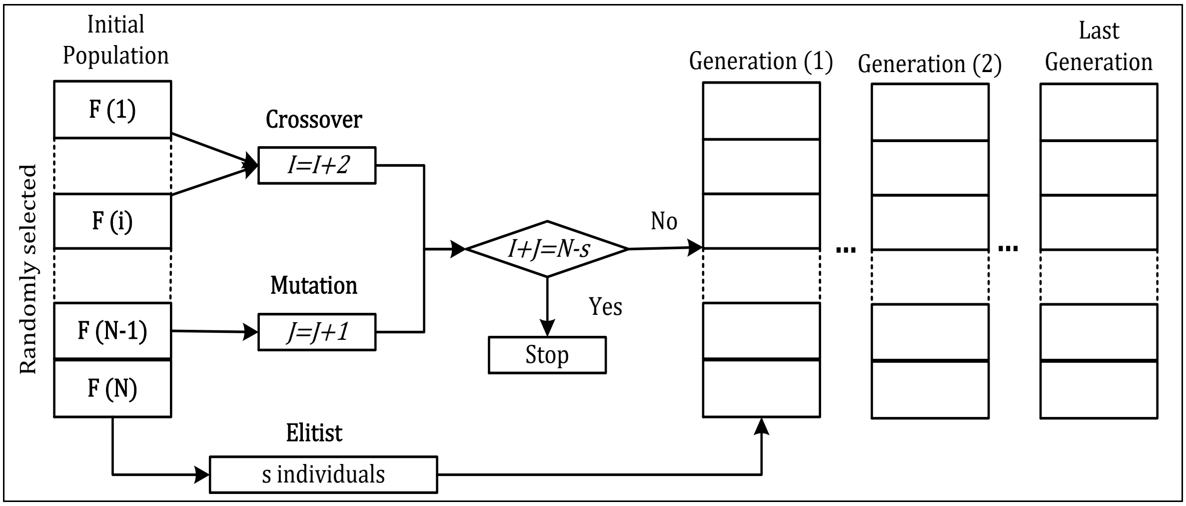

FIGURE 3. GA work flow.

$$Individual = [N_1,\ N_2, \ldots, N_{n-1}] \quad (8)$$

where N_1 is the buffer size in front of the bay of SPL's machine tool number i+1. The expression matrix is not limited, and it can be defined by any number of elements. Thus, it can deal with production systems having any number of machine tools.

In Figure 3, I refers to the number of individuals selected based on the crossover operation, in each crossover operation, two individuals are generated and sent to the next population. J refers to the number of individuals selected based on mutation operation, in each mutation operation, one individual is generated and sent to next population. S refers to the number of individuals of the next population, and these individuals selected based on elitist strategy (best individuals in current population). The detailed GA is introduced in the following steps.

Step 1: Calculate $F(i)\ \forall\ i = 1, 2, \cdots N$ for current population.

Step 2: Send s individuals to next population, $IND(i\ )\ \forall i = 1 \rightarrow s$ by applying elitist strategy.

Step3: Calculate PR (i) $\forall\ i \in POP(\ current), i = (1, \cdots, N)$ as follows:

$$PR(i) = \frac{F(i)^2}{\sum_{i=1}^{N} F(i)^2} \quad (9)$$

Step 4: Calculate $A(i)\ \forall\ i = 1, 2, \cdots N$ by using Eq. (10):

$$A(i) = \sum_{j=1}^{i} PR(i) = \sum_{j=1}^{i} \left(\frac{F(i)^2}{\sum_{i=1}^{P\_size} F(i)^2} \right) \quad (10)$$

Step 5: Calculate Period$(i)\ \forall\ i = 1, 2, \cdots IND$ as follows:

$$Period(0) = [0, A(1)]$$
$$Period(i) = [A(i-1), A(i)], \forall\ i = 1, 2, \cdots IND \quad (11)$$

Step 6: Carry out crossover operation as follows:

Step 6.1: Select two numbers between 0 and *A*(*N*) as follows:

$$N_1 \leftarrow Random\ [0, \cdots, A(N)] and$$

$$N_2 \leftarrow Random\ [0, \cdots, A(N)] \quad (12)$$
$$If\ N_1 and\ N_2 \in P(i), \forall i = 1, 2, \cdots, NI\ Then, reselect\ N_2$$

Step 6.2: Find $IND(i\ ) \in Period(i) \subset N1\ and$

$$IND(j\ ) \in Period(j) \subset N2\ , \forall\ i, j = 1, 2, \cdots IND \quad (13)$$

Step 6.3: Select crossover point, CP, as follows:

$$CP \leftarrow Random\ [1, \cdots, i, \ldots, O-1] \quad (14)$$

Step 6.4: Exchange the genes after and before CP between individuals N1 and N2.

Step 6.5: Send the generated individuals to the next population.

Step 7: Redefine the two selected periods as follows:

$$Period(i) = [A(i-1), A(i) - n]\ for\ Period(i) \subset N1\ and Period(j) = [A(j-1), A(j) - n]\ for\ Period(j) \subset N2 \quad (15)$$

Step 8: Carry out mutation operation as follows.

Step 8.1: Select a number as follows:

$$Num \leftarrow Random\ [0, \cdots, A(N)] \quad (16)$$

Step 8.2: Find $IND(i\ ) \in POP(i) \subset Num$

Step 8.3: Select two genes from the selected individual as follows.

$$a, b \leftarrow Random\ [1, \cdots, NI] \quad (17)$$

Step 8.4: Swap the values of the two selected genes.

Step 8.5: Send the generated individual to the next population.

Step 9: Redefine the endpoint of the selected period by a constant value n as follows:

$$Period(i) = [A(i-1), A(i) - n]\ for\ Period(i) \subset Num \quad (18)$$

Step 10: Repeat steps 6 to 9 to generate N – s individuals of the new population based on Cr and Mr.

Step 11: Repeat step 1 to step 10. Repeat step 11 until the fitness becomes constant. Set the individual of this fitness as the optimal individual.

Using the optimization model many sets of uptimes and down times parameters and their optimal corresponding buffer size can be generated. The Optimization toolbox in MATLAB R2019a is used to perform the optimization based on the GA.

B. PREDICTION MODEL

As formerly stated, the goal of the prediction model is to predict the optimal buffer size on the bay of each machine tools at any set of uptime and downtimes. Nevertheless, the prediction model can reduce the computational time for the buffer sizes determination. An artificial neural network (ANN) technique is utilized to develop the prediction model. ANN consists of an interconnection of simulated neurons with weights. It has the capability to acquire knowledge about the connections between inputs and outputs (cf. Figure 4) and to generalize those connections to previously unseen data. The ANN transfers a known input pattern to an output pattern by adjusting the association weight. In this research, the ANN model uses the data generated by optimization model considering the uptimes and downtimes parameters and the optimal buffer sizes associated with the highest throughput corresponding to each set of the uptimes and downtimes parameters to train the prediction model. The prediction model then will be used to predict the buffer size in a production system at any set of uptimes and downtimes.

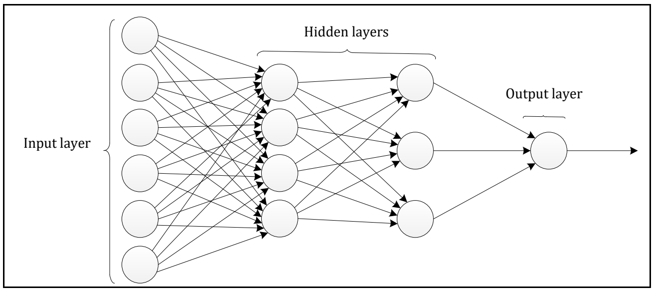

FIGURE 3. **The structure of the ANN**

The algorithm at this stage is carried out using the following steps:

Step 1: construct the ANN model.

Step 2: train the ANN with some of the buffer sizes resulted by optimization model.

Step 3: validate the ANN by the rest of the buffer sizes data.

The neural network toolbox in MATLAB R2019a is used to build the ANN model. The three layers of neural network are developed with a sigmoid activation function between the layers given in Eq. 19.

$$f(v) = \frac{1}{1+e^{-v}} \qquad (19)$$

C. INTEGRATION OF OPTIMIZATION AND PREDICTION MODELS

The optimal design of production system can be achieved by integrating the optimization model and the prediction model discussed in previous sections. The optimization model is used to generate enough data to learn the prediction model. These sets of data include different levels of uptimes and down times for all machine tools in SPL and the corresponding optimal buffer sizes that achieve the highest production rate of that SPL. After that, these data (uptimes and downtimes and corresponding buffer sizes) are fed to the prediction ANN model, by this way the prediction model can be used to predict the optimal buffer sizes at any input values of uptimes and downtimes of machine tools. Finally, the predicted buffer sizes are sent again to the optimization model to validate that the highest production rate is achieved at these predicted buffer sizes. Figure 5 shows the date flow and interaction between the optimization model and prediction model.

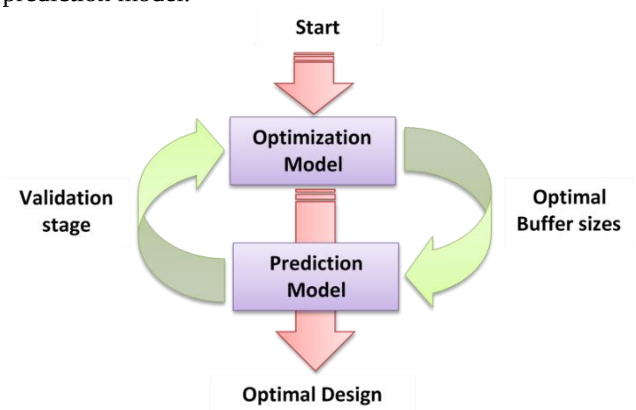

FIGURE 5. **Integration of the optimization and prediction models.**

The interaction between the GA based optimization model and the prediction ANN model is repeated to obtain the optimal or near optimal buffer size. This combination can be used to find the optimal design of the SPL during the development of the production system and support the decision of production system developer engineers regarding the selection of machine tools to achieve the goal of the production system. Furthermore, the proposed methodology can be applied to improve the production rate of a running production system, in order to address changes of uptimes and downtimes of machine tools in the production system.

V. NUMERICAL VERIFICATION RESULTS

A. SMALL PRODUCTION LINE: 5 MACHINE TOOLS

In this section, the proposed method is applied for two examples of small production lines, each with 5 machine tools with the uptimes and downtimes parameters are given in Table I. It is worth empathizing that the uptime and downtime parameters for the first case are identified based on unbiased random basis, while partially biased random procedure is followed for the second example to only ensure the uptime parameters (p_i) are always smaller than 0.5 that

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will results in large uptimes. At the same time the downtime parameters (r_i) are always kept larger than 0.5, which results in small downtimes. The difference between both examples is intended to demonstrate the feasibility of the proposed approach to predict optimal buffer sizes in two different scenarios, in which the second case expect to give a higher productivity due to the partially pre-controlled values of the uptime and downtime parameters. The maximum buffer capacity to be allocated on the bay of each machine tools is 20.

TABLE I
UPTIMES AND DOWNTIMES PARAMETERS FOR TWO DIFFERENT SPLS OF 5 MACHINE TOOLS

Example No.	Machine tool	Uptime parameter (p_i)	Downtime parameter (r_i)
#1	1	0.8147	0.9058
	2	0.6551	0.1626
	3	0.1656	0.6020
	4	0.3377	0.9001
	5	0.6225	0.5870
#2	1	0.0568	0.9432
	2	0.1378	0.8623
	3	0.0871	0.9129
	4	0.1062	0.8938
	5	0.0225	0.9775

Initially, the proposed GA randomly generated 100 sets of uptimes and downtimes for the five machine tools. Then, the proposed optimization model identifies corresponding sets of optimal buffers considering the randomly generated uptimes and downtimes parameters.

It is worth stating that the GA parameters are determined based on the guidelines presented in [40] and after some trial and error, the selected GA parameters are chosen as follows: population size of 100 individuals, crossover rate of 0.8, and mutation rate of 0.05. Figure 6 exhibits the Pareto front for the two competing objectives, productivity rate and total buffer size, described in this work, determined by the GA based optimization model.

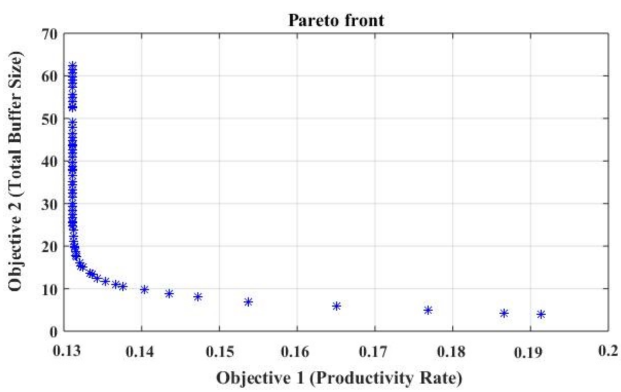

FIGURE 6. Pareto front of optimal values for optimization model of SPL with 5 machine tools.

The generated data including the uptimes and downtimes parameters and the optimal buffers are fed into the prediction model as learning and testing data. The input layer consists of 10 input neurons (uptime and downtime for each of the five machine tools). By trial and error fifty neurons' hidden layers are used which minimized the training error. The output are the four buffer sizes of the SPL.

The Levenberg-Marquardt optimization algorithm was used as a training function for the proposed ANN, which is well known as the fastest backpropagation algorithm in the Matlab toolbox, and is highly commended as a first-choice supervised algorithm. Among the input uptimes and downtimes groups and their corresponding buffer sizes obtained from optimization model, 80% of the data are used as the training group and 20% for testing. Then the ANN is applied to find the relationships between the inputs (uptimes and downtimes) and the outputs (buffer sizes). Figure 7 shows a plot regression for the proposed prediction model.

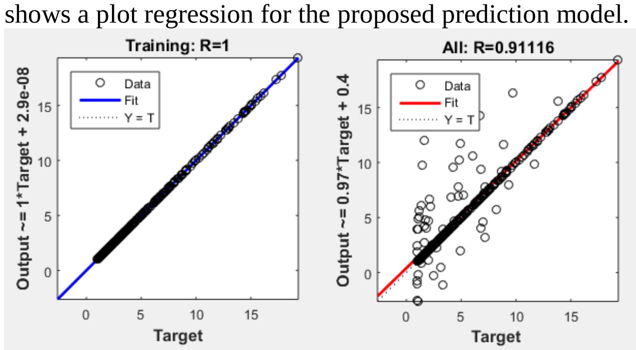

FIGURE 7. Regression analyses of outputs from the ANN for SPL of 5 machine tools during (a) the training phase and (b) the entire process (training and testing).

The optimal buffer sizes of the SPL at given uptimes and downtimes parameters resulted from the proposed integration of optimization and prediction models are given in the Table 2. However, in order to validate the results, the GA model was used to identify the optimal buffer sizes for the five machines considering the same uptimes and downtimes parameters. The obtained values for buffer sizes in both cases, using the ANN predictor and using the GA optimization model, were used to calculate associated productivity rates and all the results are presented in Table II for comparison purpose. From the results, it not so difficult to see that the prediction of buffer sizes using the two different methods are close and the final productivity rates are very similar. Besides, the results of the presented examples demonstrate the ability of the proposed approach to optimize the buffer sizes for different scenarios of uptimes and downtimes; one with unbiased random selection while the second deals with partially biased random selection of the uptimes and downtimes.

TABLE II OPTIMAL BUFFER SIZE FOR SPL OF 5 MACHINE TOOLS.

Example No.	p_i	r_i	Ni (GA & ANN)	Ni (GA only)	Productivity (GA & ANN)	Productivity (GA)
#1	0.8147, 0.6551, 0.1656, 0.3377, 0.6225	0.90586, 0.1626, 0.6020, 0.9001, 0.5870	8, 6,3, 6	7, 6, 2, 3	0.1979	0.1986
#2	0.0568, 0.1378, 0.0871, 0.1062, 0.0225	0.9432, 0.8623, 0.9129, 0.8938, 0.9775	10, 13, 11, 3	8, 10, 11, 7	0.8601	0.8581

B. LARGE PRODUCTION LINE: 15 MACHINE TOOLS

The proposed method is also applied for two examples of large production lines with 15 machine tools each. The uptimes and downtimes parameters selected for both examples are listed in Table III. Similar to the two examples presented in Table II for the small production lines of 5 machine tools, the first example of the large production line is given uptime and downtime parameters based on an unbiased random procedure, while the random selection of the uptime and downtime parameters for the second example is considered partially biased. In particular, in the second example the uptime parameters are restricted to values less than 0.5 and the downtime parameters are limited to values larger than 0.5. Again, this aims to show the ability of the proposed approach to optimize large production lines with different ranges of characteristics (uptime and downtime parameters). The maximum buffer capacity that is to be allocated on the bay of each machine tools is 20.

TABLE III
UPTIMES AND DOWNTIMES PARAMETERS FOR LARGE SPL OF 15 MACHINE TOOLS.

Example No.	Machine tool	Uptime parameter (p_i)	Downtime parameter (r_i)
#1	1	0.6238	0.1178
	2	0.7659	0.0304
	3	0.7484	0.867
	4	0.008	0.2367
	5	0.3403	0.3516
	6	0.1619	0.0418
	7	0.4812	0.5469
	8	0.9892	0.9848
	9	0.8293	0.2122
	10	0.4962	0.7812
	11	0.7573	0.4944
	12	0.2806	0.1529
	13	0.6775	0.0824
	14	0.217	0.8693
	15	0.9504	0.1473
#2	1	0.1097	0.8903
	2	0.0330	0.7032
	3	0.0800	0.6592
	4	0.1300	0.9562
	5	0.1450	0.8550
	6	0.1320	0.8680
	7	0.1961	0.8039
	8	0.1420	0.8580
	9	0.0010	0.7900
	10	0.0336	0.9664
	11	0.0850	0.8750
	12	0.0385	0.9619
	13	0.0170	0.8261
	14	0.3360	0.8013
	15	0.1897	0.8103

Similar to the previous small production line numerical example, the optimization model is applied to find the buffer sizes corresponding to many sets of uptimes and downtimes parameters. The GA parameters are similar to those mentioned in small production line numerical example. Figure 8 shows the Pareto front for the two competing objectives, productivity rate and total buffer size, determined by the GA based optimization model for the large production line.

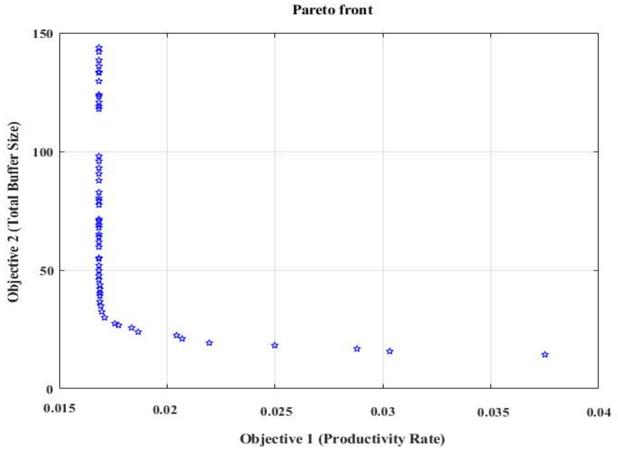

FIGURE 8. Pareto front of optimal values for optimization model of SPL with 5 machine tools.

The input layer consists of 30 inputs neurons (uptime and downtime for each of the fifteen machine tools). The output are the buffer sizes of the large SPL. Fifty neurons' hidden layers are used which minimized the training error. Similar to the ANN model for the small SPL, the Levenberg-Marquardt optimization algorithm was used as a training function for the proposed NN. Then the ANN is applied to find the relationships between the inputs and the outputs. ANN used 15% of data for both testing and validation. Figure 9 shows a plot regression for the proposed prediction model of SPL with 15 machine tools, during the training phase only (Fig. 9a) and the entire process (training and testing in Fig. 9b).

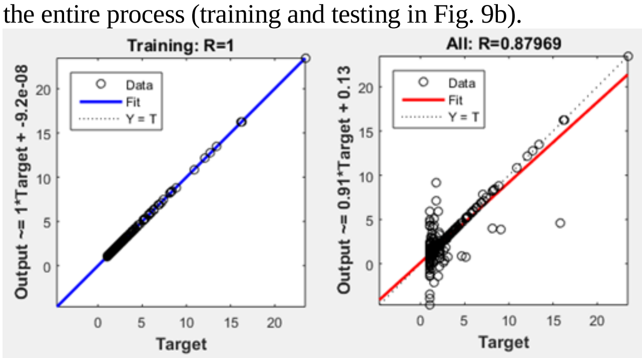

FIGURE 9. Regression analyses of outputs from the ANN for large SPL of 15 machine tools during (a) the training phase and (b) the entire process (training and testing).

Finally, the optimal buffer sizes of the SPL at given uptimes and downtimes parameters resulted from the proposed integration of optimization and prediction models for the large SPL of 15 machine tools are given in the Table 4. In addition, the optimal buffer sizes obtained using the GA only for the same uptimes and downtimes are also listed in Table IV. It is not so difficult to see that the proposed approach (GA and ANN) successfully identified buffer sizes very close to the values determined using the ANN only in both cases; with unbiased random selection of the uptimes and downtimes and when these values were partially restricted.

TABLE IV
OPTIMAL BUFFER SIZE AT GIVEN UPTIMES AND DOWNTIMES PARAMETERS FOR LARGE SPL OF 15 MACHINE TOOLS.

Example No.	p_i	r_i	Ni (GA & ANN)	Ni (GA only)	Productivity (GA & ANN)	Productivity (GA)
#1	0.6238, 0.7659, 0.7484, 0.008, 0.3403, 0.1619, 0.4812, 0.9892, 0.8293, 0.4962, 0.7573, 0.2806, 0.6775, 0.2170, 0.9504	0.1178, 0.0304, 0.8670, 0.2367, 0.3516, 0.0418, 0.5469, 0.9848, 0.2122, 0.7812, 0.4944, 0.1529, 0.0824, 0.8693, 0.1473	3, 3, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1	4, 3, 2, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1	0.0318	0.0346
#2	0.1097, 0.0330, 0.0800, 0.1300, 0.1450, 0.1320, 0.1961, 0.1420, 0.0010, 0.0336, 0.0850, 0.0385, 0.0170, 0.3360, 0.1897	0.8903, 0.7032, 0.6592, 0.9562, 0.8550, 0.8680, 0.8039, 0.8580, 0.7900, 0.9664, 0.8750, 0.9619, 0.8261, 0.8013, 0.8103	2, 2, 2, 2, 2, 4, 2, 2, 2, 2, 2, 2, 5, 11	1, 2, 5, 3, 1, 1, 3, 5, 4, 2, 2, 3, 1, 3	0.7018	0.6700

In the above two examples, it is found that the run time are 80 and 211 seconds for 5 and 15 machine tools respectively, when the codes were run on a computer system with an Intel(R) Core (TM) i7processor. The run time in all cases was quite small. In the presented numerical examples, the proposed model found the optimal or near optimal solutions for the buffer size for both short and large serial production lines. It found that the proposed model can solve the buffer size problem in a short time.

Finally, the performance of the proposed approach was compared with the state-of-the-art method for the prediction of optimal or near optimal buffer sizes for short, medium and quite large serial production lines. In particular, the results for production lines with 7, 8, 9 and 11 machine tools, with the uptimes and downtimes parameters previously reported in [41] were used as a reference for comparison with the proposed method in this research work.

The results are listed in Table VI. The maximum buffer capacity to be allocated on the bay of each machine tools is 20.

TABLE VI
COMPARISON OF OPTIMAL BUFFER SIZE AT GIVEN UPTIMES AND DOWNTIMES PARAMETERS FOR SPL OF 7, 8, 9 AND 11 MACHINE TOOLS.

No of machines	p_i	r_i	Results of the proposed method		Results from the literature [41]	
			N_i	Productivity	Ni	Productivity
7	0.06 0.07 0.03 0.02 0.08 0.06 0.04	0.75 0.74 0.88 0.86 0.81 0.8 0.85	5 3 2 3 4 2	0.8733	2 3 3 4 2 3	0.8664
8	0.01 0.01 0.02 0.03 0.02 0.01 0.01 0.02	0.6 0.6 0.55 0.6 0.55 0.6 0.6 0.6	1 3 7 5 3 1 1	0.9128	3 3 3 2 2 3 3	0.9126
9	0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1	0.8 0.8 0.8 0.8 0.8 0.8 0.8 0.8 0.8	3 3 5 2 6 3 2 2	0.7786	3 3 3 3 3 3 3 3	0.7609
11	0.2 0.22 0.25 0.1 0.15 0.17 0.23 0.24 0.2 0.18 0.14	0.83 0.86 0.85 0.94 0.93 0.95 0.86 0.84 0.9 0.95 0.87	1 2 2 2 3 2 4 4 1 2	0.6304	2 2 3 2 2 3 3 2 3 3	0.6266

Looking at the comparison between the results of the proposed approach and the results reported in the literature under the same conditions of uptimes and downtimes, one can clearly conclude that the approach presented in the papers successfully optimized the buffer sizes that lead to a higher throughput of the SPL when compared with the results presented in [41], under the same characteristics.

VI. CONCLUSION

This paper has reported on the development of an efficient prediction model to support the manufacturing engineer's decision during the design of any new SPL under specified assumptions and constraints including the uptimes and downtimes of the machine tools. The propose model also can be used to improve the design of running SPL. This study integrates the GA based optimization model and ANN based prediction models. The proposed model solves the buffer allocation problem SPL consisting of M machines and $M-1$ buffers. The results of case studies showed that the developed model accurately predict the optimal buffer size, especially for the case of five machines and even for higher number of machine tools, the results were acceptable. The proposed model is quite fast; it can solve the buffer size problem in a short time to enable a quick decision regarding the selection of buffer sizes in the production line. The run time in all cases was quite small.

The performance of the proposed approach was compared with the state-of-the-art method for the prediction of optimal or near optimal buffer sizes for short, medium and large serial production lines. The results have demonstrated that approach presented in the papers successfully optimized the buffer sizes which led to a higher throughput of the SPL when compared with the results presented in the literature, under the same characteristics.

A further investigation to improve the accuracy of the proposed model, especially for large SPL, might include other optimization tools. An extension of the work presented in this paper would be the study of other structures of production system such as production system with rework paths, split and merge production systems, assembly production systems, etc.

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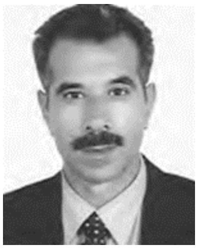

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