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Modelling and Managing "Station-Sequence" Parts Feeding in the I4.0 Era: A Simulation Approach for In-Plant Logistics

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Abstract: Parts feeding is a complex logistic problem that is further complicated by the market demand for more product variety, which forces companies and manufacturers to adopt the mixed model approach in their assembly systems. Among the parts feeding policies for mixed-model assembly systems, there is the so-called "station-sequence" policy, where stationary kits are prepared using sequences of parts that follow the sequence of the production models. This policy can reduce stocks at the assembly stations but can also lead to potential production stops due to its low robustness. The aim of this paper is to study the station-sequence parts feeding policy, focusing on its dynamic time dependence and analyzing the effects of time and model mix perturbations on the performance of the assembly system. The study was conducted through a simulation model and a statistical analysis. The final discussion also provides a set of Industry 4.0 (I4.0) enabled solutions that are able to address the negative effect of variability on the performance of the system.

Keywords: mixed-model; parts feeding; sequence; I4.0; real-time; simulation

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Citation: Faccio, M.; Granata, I.; Maretto, L. Modelling and Managing "Station-Sequence" Parts Feeding in the I4.0 Era: A Simulation Approach for In-Plant Logistics. *Appl. Sci.* **2023**, *13*, 1725. https://doi.org/10.3390/app13031725

Academic Editor: Abílio Manuel Pinho de Jesus

Received: 31 December 2022
Revised: 23 January 2023
Accepted: 25 January 2023
Published: 29 January 2023

1. Introduction

Mixed-model lines are being increasingly used within productive systems due to two related factors: (1) the increasing market demand for a greater variety of products [NO_PRINTED_FORM], and, consequently, (2) the tendency of companies and manufacturers to re-organize their processes according to the ATO (Assembly-To-Order) paradigm. Mixed-model lines allow to produce a large number of variants of a base product with the same assembly system but, at the same time, they increase the pressure on internal logistics processes. In practice, the time and productivity losses generated by missing or defective parts are far greater than for single-model assembly lines, making the correct and on-time delivery of parts to the assembly system even more crucial. Correspondingly, parts feeding systems must become more reactive to volume and mix fluctuations and they must also be able to easily accommodate the introduction of new models and components. Therefore, it is critical to study how different parts feeding policies perform in a mixed-model environment. In particular, this paper, which is an extension of the work of [1] that was presented at the 21st IFAC World Congress in 2020, will focus on the "Station-Sequence" policy.

In general, the definition of the parts feeding policy is already a significant challenge within modern assembly systems [2]. Modern parts feeding policies can be grouped into three main categories:

- The Kanban system, where assembly stations are refilled using the pull Kanban method that is based on bins that contain a fixed quantity of the same item [3].
- The travel kit system, where different parts required for the assembly of the same product are arranged in kits that follow the assembly process of the product through multiple assembly stations.
- The stationary kit, where different parts required for the assembly of multiple products are arranged in kits that are directed to a fixed assembly station.

One of the variants of the stationary kit category is the so-called "Station-Sequence" policy: in this approach, the stationary kits are created with sequences of homogeneous parts (both in terms of typology and physical attributes) that match the sequence of models that are going to be assembled. Figure 1a and 1b show the station-sequence concept and an industrial example, respectively.

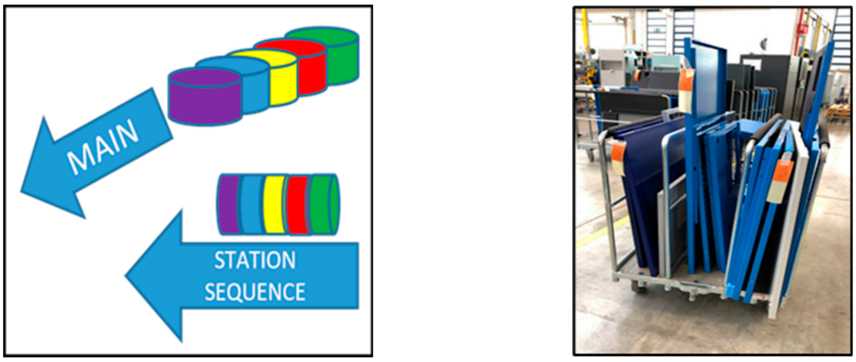

Figure 1. (**a**) A scheme of how the station-sequence policy works; (**b**) An industrial example of station-sequence application.

The station-sequence policy (from now on lowercase and without quotes), is based on the prediction of transportation orders derived from the production sequence. The predicted transportation orders are then used to dynamically generate the tours for the supply of the required parts from the warehouse to the assembly stations. Reference [4] showed that the main differentiating parameter between different parts feeding policies is represented by the total handling time: it includes both the time spent at the warehouse (material handling time at the warehouse), mainly in material preparation, and the time spent at assembly stations (material handling time at assembly stations) for parts picking and placing. With regard to the variation of these two material handling times across the aforementioned categories of parts feeding policies, the literature shows two opposing trends:

a. The material-handling time at the warehouse increases moving from a Kanban system to a kitting system, due to the increased number of picks that are necessary for the creation of the kits [5,6].
b. The material-handling time at assembly stations decreases moving from a Kanban system to a kitting system. In a kitting system, in fact, fewer materials are stored at the assembly station, meaning they can be placed closer to the operator, reducing the fetching time and hence increasing productivity [7].

The station-sequence parts feeding policy is particularly interesting since it retains the low material-handling time at assembly stations typical of kitting systems and combines it with a reduced material-handling time at the warehouse. The low handling time at the warehouse is achieved since the parts that are picked for the preparation of the kits, that belong to the same station sequence, are of the same typology, which are usually stored close to each other. The proximity of the picked parts has a strong positive effect on the picking time because it significantly reduces the distance traveled by the picker. In fact, according to [8], traveling activity accounts for roughly 50% of the total manual picking time.

However, the station-sequence feeding policy also suffers from three main drawbacks, which are all related to low levels of the station-sequence stock:

- A lack of flexibility to the change of sequence and mix of the assembled models. If the stock of the station sequence is low, the probability to stop the assembly as a consequence of even one missing part increases when the sequence of assembled models changes.

- A lack of flexibility toward variations in the assembly line cycle time. If the stock of the station sequence is low, the probability to stop the assembly as a consequence of even one missing part increases when the assembly line cycle time has significant variations.
- A lack of flexibility with respect to the variation of the parts feeding period. If the stock of the station sequence is low, the probability to stop the assembly as a consequence of even one missing part increases when the parts feeding period has significant variations.

In this paper we are going to study the station-sequence parts feeding policy considering its dynamic time-dependence and we are going to analyze how its performance is affected by perturbations of both the assembly line cycle time and the parts feeding period, as well as by changes in the model mix. This study was carried out through a set of simulations, as suggested in other contributions such as [9], implemented on Siemens' Plant Simulation. The main results are the quantitative definition of the main influencing factors and their impact on system performance. Finally, we provide a brief discussion on how Industry 4.0 technologies can improve the operations of a company that adopts a station-sequence parts feeding policy.

The rest of the paper is structured in this way: Section 2 reports the literature review, Section 3 describes the simulation model, Section 4 discusses the results of the simulation, Section 5 introduces the main possibilities according to I4.0 implementation and Section 6 presents the conclusions.

2. Literature Review

In mixed-model assembly lines, planning problems can be grouped into two main categories: medium-long-term problems and short-term problems. The former category includes the design of the assembly line, line balancing, production planning, or materials procurement. The latter category can be further divided into three other sub-problems [10]:

- Production sequencing: defining the best sequence of models for each production interval.
- Material flow control: ensuring the timely release of parts from suppliers as well as the timely delivery of parts to the right assembly stations.
- Resequencing: applying changes to the production sequence in case of disruptions.

The parts feeding problem theoretically belongs to the material flow control sub-category. However, according to [11], the parts feeding problem ends up being strongly related also with the production sequencing and resequencing sub-categories. Moreover, all three short-term problems sub-categories show a clear dynamic time-dependence, which becomes even more critical when the adopted parts feeding policy is the station sequence, as shown in the Introduction. However, the literature has addressed the parts feeding problem in mixed model assembly lines mainly from a static perspective, neglecting the dynamic aspects and focusing instead on variables and parameters such as parts attributes, frequency of parts consumption, or parts cost. In practice, many contributions have adopted this perspective, starting from [12]. For a comprehensive literature review of parts feeding policy selection, it is possible to look at [13] as well as [14]. Qualitative factors, such as product and component volume, variety, and size, were adopted as policy selection criteria in [15]. Conversely, many other works adopted quantitative comparison models for the selection of the most appropriate parts feeding policy ([4,6,16,17]). More recent examples include [18], which focused on the development of a cost model for kitting, Kanban, and line stocking, that was based on qualitative parts features: unit size and cost. Reference [19] developed a combined methodology, which starts with a hierarchical cluster analysis that is followed by an activity-based costing methodology, able to select the best-performing parts feeding system.

Fewer works have attempted to integrate the study of parts feeding policies in mixed-model assembly lines with the inclusion of dynamic elements. The first contribution of this kind is [20], which proposed a two-stage heuristic procedure; in the first of the two stages, transportation orders were determined according to the expected part consumption rates. Reference [21] explored the optimal loading of tow trains from a Just-In-Time perspective. A mathematical model was developed with two objective functions, aimed at minimizing the number of bins at the stations and the number of surplus bins. A computational study was also conducted, introducing variability into elements such as parts demand or bin capacity. The results showed that increasing the delivery frequency reduces inventory or requires fewer wagons per train. This effect diminishes when delivery schedules become denser. Reference [10] focused on a paced mixed-model line. A mixed integer model was developed, and it was tested in a simulation scenario that included various dynamic elements of variability: three levels of problem instances (number of stations, models, and line sections), three degrees of parts variability, and two levels of load length of bins, buffer storage at the stations, size of unit loads and initial inventory at the stations. The results showed that the high variability of parts demand at the line stations, derived from the continuous changes in the daily production sequences, represents an additional difficulty in the management of station-sequence assembly lines. As a consequence, the exact timing of the material supply acquires even more importance. Reference [22] developed a framework for the design of an integrated supermarket and feeding system for mixed-model assembly lines that included, in the second stage, the evaluation of the dynamic aspects of the problem. A case study based on an automotive production line was presented, and an analysis of the effects of the variability of fleet size, tow train capacity, and tow train loading interval was conducted.

The most recent contributions that included the dynamic aspect within the parts feeding problem in mixed-model assembly lines focused on two main directions: (1) the scheduling problem of internal vehicles and (2) the development of multi-objective models that include the evaluation of energy consumption, which is part of a broader tendency towards the incorporation of sustainability within the productive sector [23]. Works that fall within the first research direction are: [24–27]. For example, reference [25] investigated the dynamic scheduling of tow trains in an automotive assembly line, with the objective of minimizing the weighted sum of the assembly line throughput and the material delivery distance. A simulation model of the real assembly line was developed using Plant Simulation in order to generate training samples based on the system parameters configuration; reference [27] studied the dynamic parts feeding scheduling problem in an automotive mixed model assembly line under a Kanban-based parts feeding policy, considering also the dynamic disturbances of the assembly lines. The considered dynamic disturbances were: variations of the production mix, variations in the weights of the scheduling criteria, maintenance of AGVs, and short-term adjustment of the production sequence. Contributions that followed the second research direction are: [28–30]. For example, reference [30] aimed to improve the scheduling algorithm that governs mobile robots by including their energy consumption in the operational criteria, in order to optimize the overall energy efficiency and sustainability of the parts feeding system. Two other recent contributions did not follow the two mentioned directions but explored other themes: reference [31] studied the concept of line-integrated supermarkets combining station assignment and operator scheduling problems, including in their work the dynamic variability of the demand at the stations and the variability in the capacity of both bins and operators; reference [32] focused on an even more short-term decision level: the launch control of a new car model in a mixed-model assembly line under real-time conditions (which include variations of the processing times and setup costs).

In conclusion, in the extant literature on parts feeding policies for mixed-model assembly lines, there are a few gaps that can be summarized as follows:

- Few studies focused on the dynamic aspect of the parts feeding problem.
- The studies that included dynamic elements, especially the most recent ones, focused almost exclusively on the scheduling problem of internal vehicles or on the development of multi-objective models that include energy consumption.

- There are no studies on the station-sequence policy, despite its wide adoption in the industrial world.

Considering these gaps, we can therefore state that, to the best of our knowledge, this paper represents the first work to perform a deep assessment of the station-sequence feeding policy, as well as being the first to study its dynamic time dependence and the evaluation of the impact of such dependence on the performance of the system.

3. Modeling of the Station-Sequence Feeding Policy

In order to analyze how the performance of a mixed model assembly system, working under the station-sequence parts feeding policy, is affected by dynamic time perturbations and variations of the model mix, an assembly line is modeled with the aid of simulation software. The chosen software was Plant Simulation

The simulation model includes five assembly stations where three different models (M1, M2, and M3) can be assembled. The assembly system, represented in Figure 2, was modeled according to the following set of assumptions:

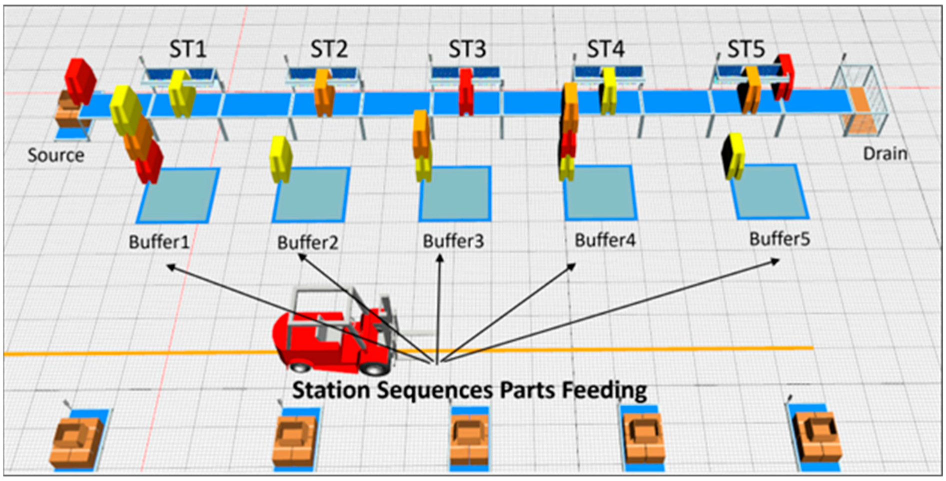

Figure 2. Representation of the modeled assembly system.

- The modeled system is a mixed-model assembly line that includes a buffer between the parts feeding system and each assembly station. This buffer stores the sequences of parts that constitute the "station sequence".
- There is a buffer along the assembly line between each pair of assembly stations.
- The station sequence follows the predicted models mix of the assembly line.
- The sequence for each station considers one part for each model at a time.
- The time distribution of both the assembly line cycle time and the parts feeding period are considered stochastic with uniform distribution (this assumption will be clarified below once the input parameters of the simulation model are introduced).

Reference [10] suggested that the variations of the model mix alongside the perturbations of the timing of the materials supply to the stations can have a significant impact on the performance of the assembly system when the parts feeding policy is the station sequence. Therefore, in order to examine this link in depth, the following parameters were considered as variables in our simulation model:

- The assembly line cycle time.
- The parts feeding period.
- The sequences of the model mix.

These variables were formalized with the five following inputs of the simulation model (the complete set of notations adopted in the simulation are reported in Table 1):

- $ALCT_i$, average assembly line cycle time.

- $ALCTV_i$, variation in the assembly line cycle time.
- FP_i, average parts feeding period.
- $PFCTV_i$, variation of the parts feeding period.
- SEQ_i, variation in the model sequence.

Table 1. Adopted notations.

Symbol	**Description**
$id = 1, \ldots I$	Simulation scenario ID Index
$n = 1, \ldots, N$	Assembly station index
$ALCT_i$	Assembly Line average Cycle Time of scenario *i* [s/piece]
$ALCTV_i$	Assembly line cycle time variation compared to the average cycle time of scenario *i* [± s/piece]
FP_i	Average parts feeding period of scenario *i* [s/sequence]
$PFCTV_i$	Parts feeding period variation compared to the average parts feeding period of scenario *i* [±s/sequence]
PFQ_i	Parts fed for each feeding period [parts/feeding period]
SEQ_i	Models sequence of scenario *i*
$PFSEQ_i$	Parts feeding sequence of scenario *i*
$BS_{n,i}$	Maximum parts quantity within the parts buffer for station *n* of scenario *i* [pieces]
BS_i	Total Maximum parts quantity within the parts buffers of scenario *i* [pieces]
$W_{n,i}$	Working time for station n of scenario *i* [%]
THR_i	Total throughput during the simulation period of scenario *i* [pieces]
$MinBS$	Minimum value of the total buffer content [pieces]
Max	Maximum value of the total throughput [pieces]
W_i	Average stations working time of scenario *i* [%·100]
T_i	Relative total throughput [%·100]
B_i	Relative total Buffer Content [%·100]

Different levels of the input parameters were defined. For example, the variation of the assembly line cycle time ($ALCTV_i$) can assume three different values: 0, 30, or 60 s/piece. These values correspond respectively to a 0%, 50%, or 100% variation of the assembly line cycle time. This approach allows the normalization of the results: the output of a simulation run can be interpreted as the output of a generic multi-model assembly line characterized by 0%, 50%, or 100% variation of the assembly line cycle time, providing a normalized outlook of the results for practitioners. A similar approach was adopted for the definition of the levels of variation in the parts feeding period. A complete overview of the input parameters and their variability is offered in Table 2. The input parameters and their variability were then combined in order to conduct a multi-scenario analysis. The total number of tested scenarios was $I = 486$, where each scenario corresponds to a complete run of the simulation model. An overview of the simulation results is offered in Table 3, where each row corresponds to a specific scenario, while the columns report both the input parameters and the simulation results.

Table 2. Simulation parameters.

Parameter	**Value**	*Parameter*	**Value**
Simulation time	4 h	FP_i	[180; 1800; 3600] s/sequence
Assembly Stations	5 Stations	*PFCTV*	±[0; 30; 60; 900; 1800; 3600] s/sequence
Models Number	3 Models	$PFSEQ_i$	[1M1, 1M2, 1M3]
ALCT	60 s/piece	SEQ_i	[1M1, 1M2, 1M3]; [1M1, 1M2, 2M3]; [1M1, 1M2, 3M3]; [1M1, 2M2, 2M3]; [1M1, 3M2, 3M3]; Random
ALCTV	± [0; 30; 60] s/piece		

Table 3. Example of the simulation inputs and outputs for each tested scenario. The first column represents the scenario index, columns 2 to 6 collect the different values of the input parameters, and the remaining columns list the simulation results.

ID	ALCTi	ALCTVi	FPi	PFCTVi	SEQi	BS1i	BS2i	BS3i	BS4i	BS5i	W1i	W2i	W3i	W4i	W5i	THRi	BSi	PFQi	Wi	Ti	Bi
1	60	0	180	0	1 M1,1 M2,1 M3	4	4	4	4	4	99.6%	99.2%	98.7%	98.3%	97.9%	233	20	3	98.7%	1.00	1.00
2	60	30	180	0	1 M1,1 M2,1 M3	8	8	8	8	8	97.6%	97.2%	96.7%	96.3%	95.9%	229	40	3	96.7%	0.98	2.00
3	60	60	180	0	1 M1,1 M2,1 M3	13	13	13	13	13	95.6%	95.1%	94.7%	94.3%	93.9%	224	65	3	94.7%	0.96	3.25
7	60	0	180	0	1 M1,1 M2,2 M3	80	81	81	81	81	66.7%	66.7%	66.7%	66.2%	65.8%	156	404	3	66.4%	0.67	20.20
8	60	0	180	0	1 M1,1 M2,3 M3	107	108	108	107	107	55.8%	55.8%	55.4%	55.0%	55.0%	130	537	3	55.4%	0.56	26.85
9	60	0	180	0	1 M1,2 M2,2 M3	41	42	42	42	42	83.3%	83.3%	82.9%	82.5%	82.1%	195	209	3	82.8%	0.84	10.45
10	60	0	180	0	1 M1,3 M2,3 M3	54	55	55	55	55	77.9%	77.9%	77.5%	77.1%	76.7%	182	274	3	77.4%	0.78	13.70
11	60	30	180	0	1 M1,1 M2,2 M3	80	81	81	81	81	66.7%	66.7%	66.7%	66.2%	65.8%	156	404	3	66.4%	0.67	20.20
12	60	30	180	0	1 M1,1 M2,3 M3	107	108	108	107	107	55.8%	55.8%	55.4%	55.0%	55.0%	130	537	3	55.4%	0.56	26.85
13	60	30	180	0	1 M1,3 M2,3 M3	54	55	55	55	55	77.9%	77.9%	77.5%	77.1%	76.7%	182	274	3	77.4%	0.78	13.70
14	60	60	180	0	1 M1,1 M2,2 M3	80	81	81	81	81	66.7%	66.7%	66.7%	66.2%	65.8%	156	404	3	66.4%	0.67	20.20
15	60	60	180	0	1 M1,1 M2,3 M3	107	108	108	107	107	55.8%	55.8%	55.4%	55.0%	55.0%	130	537	3	55.4%	0.56	26.85
16	60	60	180	0	1 M1,2 M2,2 M3	41	42	42	42	42	83.3%	83.3%	82.9%	82.5%	82.1%	195	209	3	82.8%	0.84	10.45
17	60	60	180	0	1 M1,3 M2,3 M3	54	55	55	55	55	77.9%	77.9%	77.5%	77.1%	76.7%	182	274	3	77.4%	0.78	13.70
18	60	0	1800	0	1 M1,1 M2,1 M3	30	30	30	30	30	99.6%	99.2%	98.7%	98.3%	97.9%	233	150	30	98.7%	1.00	7.50
19	60	30	1800	0	1 M1,1 M2,1 M3	35	35	35	35	35	97.7%	97.3%	96.9%	96.5%	96.1%	229	175	30	96.9%	0.98	8.75
20	60	60	1800	0	1 M1,1 M2,1 M3	39	39	39	39	39	95.9%	95.5%	95.1%	94.7%	94.2%	225	195	30	95.1%	0.97	9.75
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…

The output parameters of the simulation, reported in Table 3, are calculated as follows with Formulas (1)–(7) (please refer again to Table 1 for the complete description of the adopted notations):

$$PFQ_i = \frac{FP_i}{ALCT_i} \tag{1}$$

$$BS_i = \sum_n BS_{n,i} \tag{2}$$

$$MinBS = Min[BS_i] \tag{3}$$

$$MaxT = Max[THR_i] \tag{4}$$

$$W_i = \sum_n \frac{W_{n,i}}{N} \tag{5}$$

$$T_i = \frac{THR_i}{MaxT} \tag{6}$$

$$B_i = \frac{BS_i}{MinBs} \tag{7}$$

Out of the seven reported output parameters, three were considered as main indicators of the performance of the assembly system since they represent the overall performance of the system in terms of working time, throughput, and buffer content, and were used for the subsequent statistical analysis:

- W_i, the average station working time.
- T_i, relative total throughput.

B_i, relative total buffer content. Theoretically, the best possible simulation scenario would be the one where the average station working time W_i is maximized, the relative total throughput T_i is maximized, and the relative total buffer content B_i is minimized.

4. Discussion of the Simulation Results

Statistical analysis was conducted on the simulation results in order to understand the impact that time perturbations (such as *ALCTV*, *FP,* and *PFCTV*) and model mix perturbations (*SEQ*) have on the performance of the assembly system (measured by the aforementioned parameters *W*, *T*, and *B*).

Inferential analysis was conducted first, in order to quantify the magnitude of the effects of the input variables on the simulation outputs. Then, an ANOVA analysis was performed, aimed at the determination of the interactions between input and output parameters. With regards to the inferential analysis, a Pareto chart of the standardized effects was drawn for each output parameter (*T*, *W,* and *B)* and is represented in Figures 3–5 respectively. The interaction plots of the ANOVA analysis are also reported for each considered output parameter (*T*, *W,* and *B)* and presented in Figures 6–8 respectively.

With relation to the total throughput *T*, Figure 3 shows that the input variables that have a significant effect on the output are mainly *SEQ* and *PFCTV*, followed by the interaction of *FP* and *PFCTV*, *FP* and the interactions *PFCTV-SEQ*, *FP-SEQ*, *FP-PFCTV-SEQ*. Focusing on the main influencing factors, the trends shown in Figure 6 indicate that the larger the deviation of both *SEQ* and *PFCTV* from their nominal values, the larger the reduction of the mean of the total throughput *T*. With regard to the *FP-PFCTV* interaction, Figure 6 indicates that the larger *FP*, the bigger the effect of *PFCTV* on the reduction of the throughput *T*, and vice versa.

Similar considerations can be drawn for the average station working time *W*. Figure 4 shows that the input variables that have a significant effect on the output are mostly *SEQ* and *PFCTV*, followed by the interaction *SEQ-PFCTV* and then by *FP-PFCTV*, *FP*, *FP-SEQ*, and *FP-PFCTV-SEQ*. Again, the trends represented in Figure 7 show that deviating from the nominal values of both *SEQ* and *PFCTV* ends up reducing the mean of the average station working time *W*.

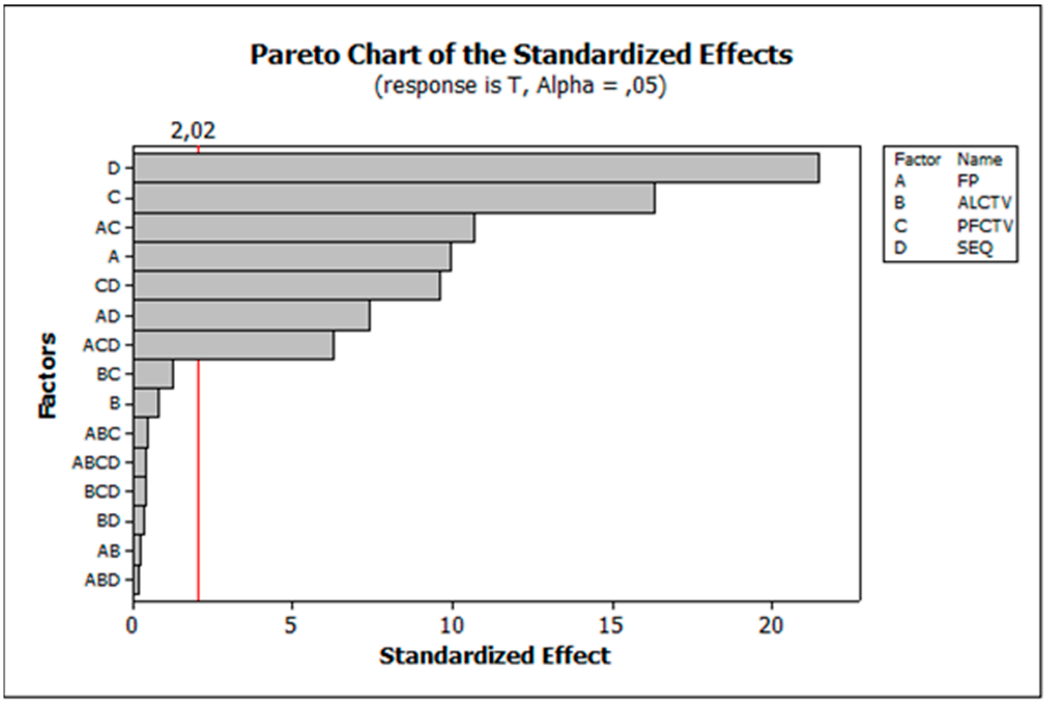

Figure 3. Pareto chart of the standardized effects of the inputs on *T*.

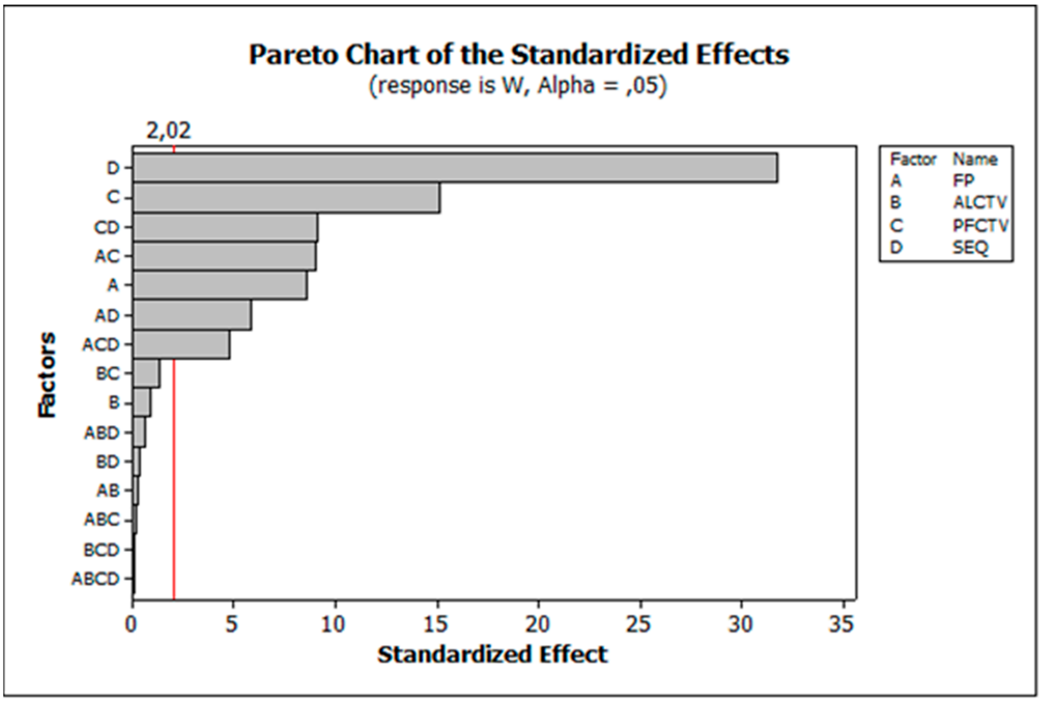

Figure 4. Pareto chart of the standardized effects of the inputs on *W*.

Finally, for the last output parameter *B*, the total buffer content, Figure 5 shows that the main influencing variables are *SEQ*, *ALCTV*, and *PFCTV*, followed by *FP-SEQ*, *PFCTV-SEQ*, *FP-PFCTV*, and *FP-PFCTV-SEQ*. The trends reported in Figure 8 indicate that a deviation from the nominal value of the three main influencing factors (*SEQ*, *ALCTV*, and *PFCTV*) results in an increase of the mean of the total buffer content *B*.

To visualize the relations between the values of the three output parameters across different simulation scenarios, a contour plot is shown in Figure 9: *W* and *B* are represented on the x- and y-axis, respectively, while different levels of the value of *T* are represented in a green-shading scale.

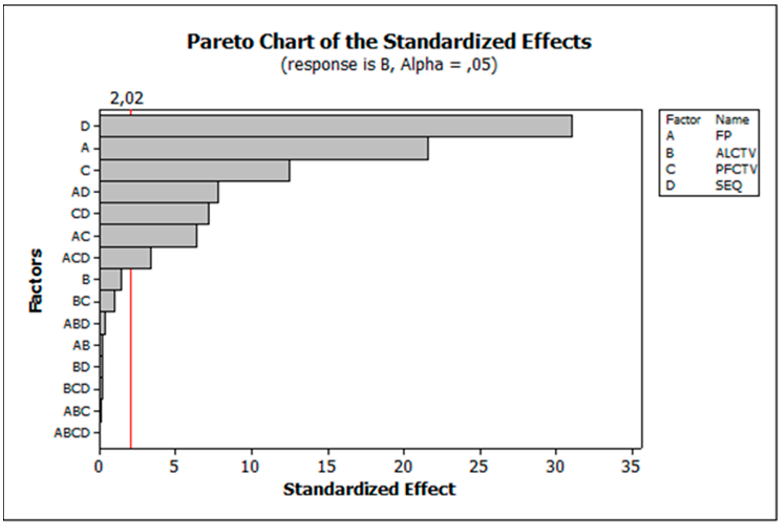

Figure 5. Pareto chart of the standardized effects of the inputs on *B*.

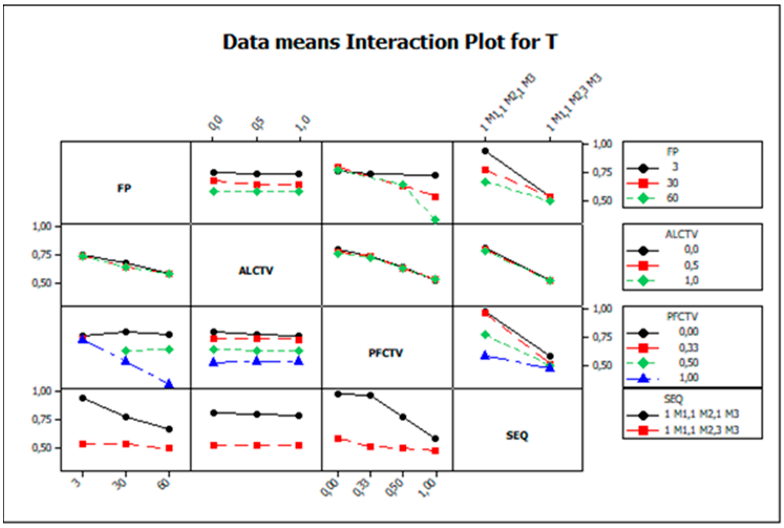

Figure 6. Interaction plot of the input parameters *FP*, *ALCTV*, *PFCTV*, *SEQ* for *T*.

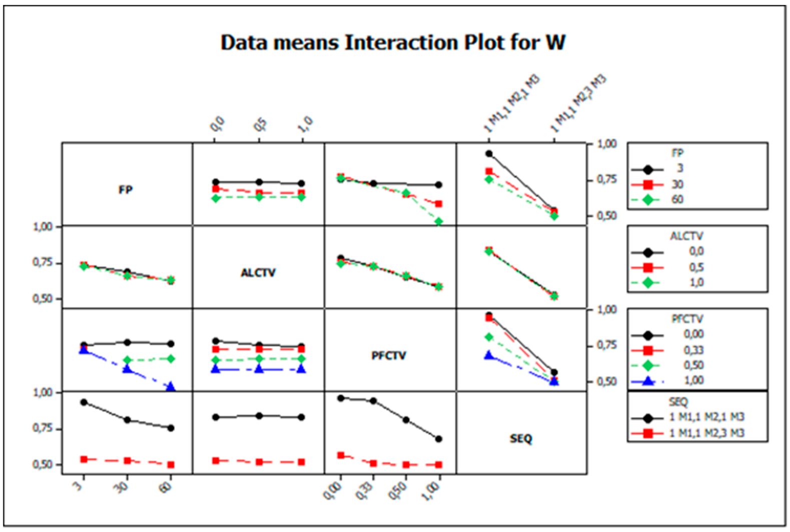

Figure 7. Interaction plot of the input parameters *FP*, *ALCTV*, *PFCTV*, *SEQ* for *W*.

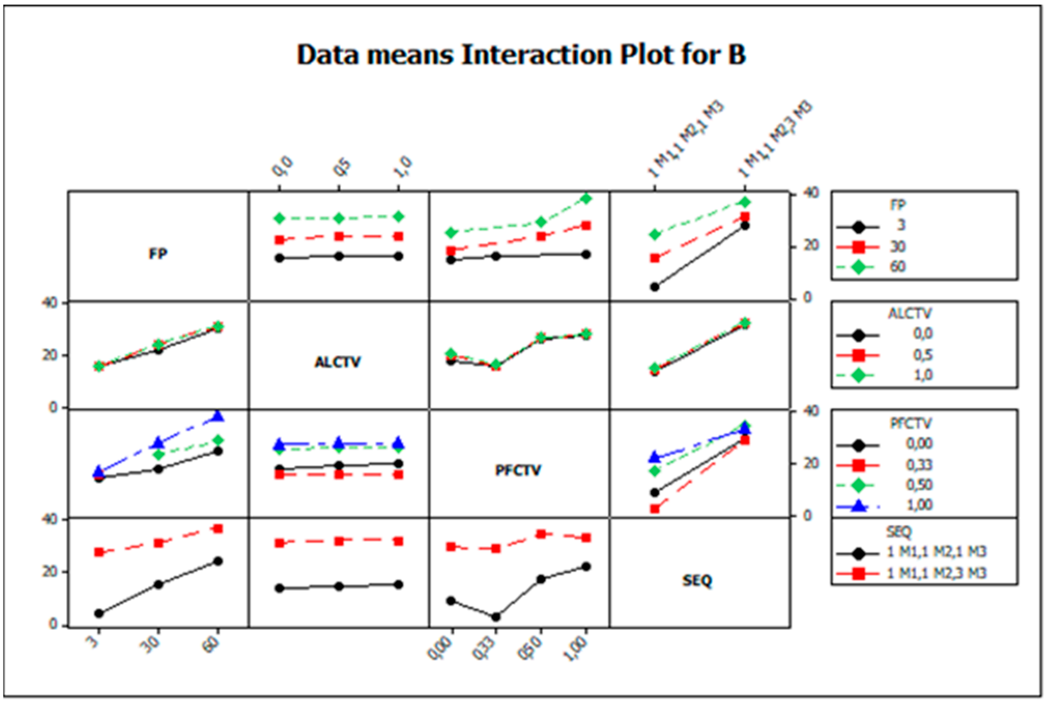

Figure 8. Interaction plot of the input parameters *FP*, *ALCTV*, *PFCTV*, *SEQ* for *B*.

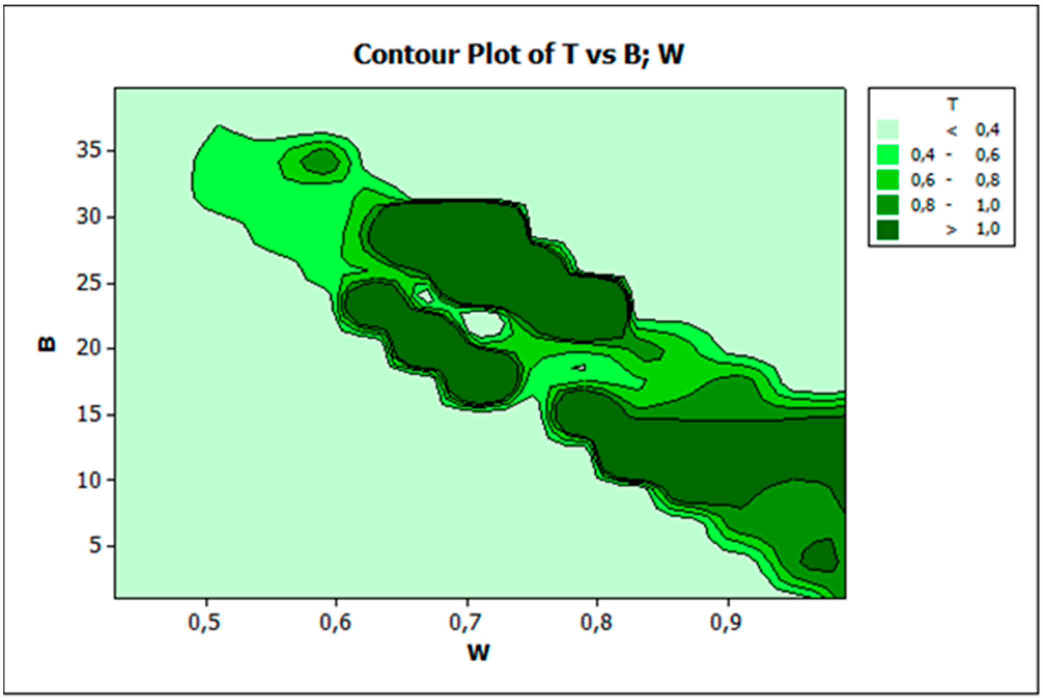

Figure 9. Contour plot of *T* versus *B* and *W*.

Figure 9 shows that there is a set of scenarios where all three main output parameters tend towards their theoretical optimum at the same time: *T* and *W* are maximized, and *B* is minimized. These scenarios are represented in dark green in the bottom-right corner of Figure 9. There are also two other areas, however, where the highest values of *T* do not correspond to the minimum values of *B* or the maximum values of *W*: they are the two dark green areas at the center of Figure 9. In these scenarios, the maximum values of throughput can be reached even if the total buffer content and the average station working time are sub-optimal.

5. Industry 4.0 Solutions

Table 4 offers a summary of the results of the statistical analysis and provides a set of process variability management solutions that are empowered by the adoption of Industry 4.0 technologies. The first column of the table includes the main input parameters (*SEQ*, *PFCTV*, *FP*, *ALCTV*) and refers, in particular, to their variations. The second and third columns report the effects in terms of the impact level of the variability of a certain input parameter on all three main output parameters (*T*, *W*, *B*). The negative impact level is represented with the aid of a set of black dots: the more dots, the worse the negative impact of the variability of the input on the output parameter. The fourth column indicates the Industry 4.0 technologies that can be adopted to address the process variability issue. The reported technologies were chosen from—and were consequently numbered according to—the classification proposed in [33]: this is one of the most widely adopted Industry 4.0 classifications, coming from one of the most cited scientific articles on the topic, and it provides a rather wide list of (up to 32) Industry 4.0 technologies. The fifth, and last, column shows how the I4.0 technologies can be combined in order to provide an effective solution to the process variability.

Table 4. Summary of the negative impact level of the variations of the input over the output parameters and possible solutions enabled by the adoption of Industry 4.0 technologies.

Input Variations.	Output	Negative Impact Level	Useful I4.0 Technologies	Possible I4.0 Solutions
SEQ	T W B	●●●● ●●●● ●●●●	1. Sensors 7. Simulation of processes 10. Machine-to-Machine communication 13. Traceability of raw materials 14. Traceability of final products 22. Remote monitoring of production 23. Remote operation of production	1-Introduce sensors within assembly lines to monitor the real sequences of models and parts at assembly stations. 2-Compare in real time model sequences with planned sequences. 3-Compare in real time parts sequences withplanned sequences. 4-Send real-time information to the parts feeder at the warehouse highlighting if real-time models and parts sequences in the assembly line are different from planned ones. 5-Act accordingly
PFCTV	T W B	●●● ●●● ●●	1. Sensors 7. Simulation of processes 10. Machine-to-Machine communication 13. Traceability of raw materials 22. Remote monitoring of production 23. Remote operation of production	1-Introduce sensors on tow trains to monitor the real-time positions across the routes. 2-Compare the real-time positions with the planned positions according to the parts feeding cycle time. 3- Send real-time information to tow trains operators4-Act accordingly

Table 4. *Cont.*

Input Variations.	Output	Negative Impact Level	Useful I4.0 Technologies	Possible I4.0 Solutions
FP	T W B	●● ●● ●●●	11. Industrial Robots (including AGVs)	1-Minimize feeding period by reducing the tow train routes and increasing the number of tow trains using Automated Guided Vehicles.
ALCTV	T W B	● ● ●	1. Sensors 7. Simulation of processes 10. Machine-to-Machine communication 13. Traceability of raw materials 22. Remote monitoring of production 23. Remote operation of production	1-Introduce sensors within assembly lines to monitor the assembly stations takt time. 2-Compare the real-time takt time with the planned takt time. 3- Send real-time information to assembly stations. 4-Act accordingly

For example, let's focus on the first input parameter: the models sequence variation *SEQ*. *SEQ* has the worst negative impact level on all three output parameters, as indicated by ●●●●. An intuitive solution would be to freeze the sequence of models for long periods of time. However, the current market is characterized by large variability in demand, which forces productive systems to be as reactive as possible to changes, making the freezing solution impractical. To address this variability, it would be ideal to monitor in real time the actual progress of the products on the assembly line, taking immediate action in the case of variations in order to minimize the time in which the system remains out of its nominal conditions. Conveniently, Industry 4.0 technologies allow companies to do exactly that. In the case of addressing the variability of the models sequence, the technologies that were chosen from the classification of [33] were: (1) Sensors, (7) Simulation of processes, (10) Machine-to-machine communication, (13) Traceability of raw materials, (14) Traceability of final products, (22) Remote monitoring of production, and (23) Remote operation of production. The combination of these seven technologies empowers the following solutions:

1. Introduce sensors within assembly lines (such as RFID and RFID readers or barcode and barcode readers or, in general, sensors that can guarantee the traceability of materials along the assembly line) to monitor the real sequences of models and parts at assembly stations.
2. Compare in real time the model sequences with the planned sequences.
3. Compare in real time the parts sequences with the planned sequences.
4. Send real-time information to the parts feeder at the warehouse highlighting if real-time models and parts sequences in the assembly line are different from planned ones.
5. Act accordingly (for example, correct immediately any discrepancies between the planned and real-time sequences, both at the warehouse and the assembly station level)

By implementing this five-point solution plan, it is possible to restore the system to its nominal state, reducing the negative impact on the output parameters *T*, *W*, and *B*.

Similar considerations are then provided in Table 4 for the other remaining input variables *PFCTV*, *FP*, and *ALCTV*.

6. Conclusions

This paper provides an in-depth analysis of the station-sequence parts feeding policy, focusing on its dynamic time dependence and analyzing the effects of time and model mix perturbations on the performance of a mixed-model assembly system. A simulation study was conducted, generating a simulation model of an assembly line with five assembly stations where three different models are assembled. The simulation model included five main input parameters (assembly line average cycle time, assembly line cycle time variation, average parts feeding period, parts feeding period variation, and models sequence variation) and three output parameters (average stations working time, relative total throughput, and relative total buffer content). The input parameters were then combined into a wide set of simulation scenarios. Once all the scenarios had been tested, a statistical analysis of the results of the simulation was conducted, identifying the main influencing factors and their effects on the performance of the system. Finally, the negative effects on the performance of the system were addressed with a set of specifically designed, I4.0-enabled solutions.

Author Contributions: Conceptualization, M.F.; methodology, M.F.; software, M.F.; validation, M.F.; formal analysis, M.F.; investigation, M.F.; data curation, M.F.; writing—original draft preparation, M.F., L.M., I.G.; writing—review and editing, M.F., L.M., I.G.; supervision, M.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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