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Implementing Job Sequencing in a CONWIP fully automated assembly line

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Abstract. Electric vehicle production poses several challenges from the manufacturing point of view due to the uncertainty in the price and availability of raw materials and the frequent fluctuations of market demand. Moreover, mass customisation requires flexible and reconfigurable manufacturing systems, while the automation of the assembly lines to achieve a higher throughput rate and the complexity of job handling require conveyors and carousels. This paper investigates the implementation of job sequencing policies through conveyor loops to improve the flexibility and reconfigurability of a realistic CONWIP assembly line while avoiding upstream and downstream variability propagation. Scenario analysis evaluates how different job sequencing strategies and WIP control can impact the average and standard deviation of the shift throughput, the average job flow time, and the probability of deadlocks on an assembly line for stators of electric engines.

Introduction

Improving the manufacturing system flexibility and reconfigurability while reducing upstream and downstream variability propagation is important in all the industrial fields where there is pressure for mass customisation[1], and the raw material supplies and demand are critical[2]. Mass customisation requires flexible and reconfigurable systems to produce many product variants [3], which are subjected to frequent fluctuations in demand. Moreover, some industrial fields also have an intrinsic demand variability due to many causes, such as fast obsolescence rate, technology disruptions, highly depreciable raw materials, and product demand depending on public incentives like electric car manufacturing [4].

In electric vehicle manufacturing, raw materials supplies are unstable because of the uncertainties in the availability and prices of critical raw materials, such as neodymium and dysprosium, essential for electric motors, due to their global scarcity and the geopolitical context [5]. From the point of view of production planning, increasing flexibility and reconfigurability while reducing variability propagation means changing the system throughput (TH) based on the product currently in production, its demand fluctuations, and the congestion of the downside subsystems [6] while mitigating the impacts of the fluctuations in raw material consumption rates [7].

Discrete event simulation and scenario analysis have been exploited to investigate job sequencing strategies in a part of a realistic assembly line for electric vehicle engines using a CONstant Work-In-Progress (CONWIP) logic. CONWIP systems have a fixed number of jobs, namely the WIP (W*), allowing a new part to enter the system only when a finished one leaves. In particular, the paper studies the impacts of combining different job sequencing strategies in different system workstations on the average shift TH, its standard deviation, the flowtime (FT), i.e., the total time of a job within the line, and the occurrence of disruptive events when changing TH.

In the remainder, the Background section provides the research context through the review of the scientific literature, while the Problem description section introduces the industrial problem, the case study, the proposed approach and the design of experiment. The Results and the Conclusion sections discuss the experimental insights and conclude the paper, respectively.

Background

In general, a CONWIP logic is unsuitable for multi-product environments and lines with non-reliable machines because the position of the jobs within the system is scarcely predictable, with the risk of unbalancing the line [8]. Moreover, the workstation layout that facilitates system flexibility and reconfigurability is the matrix, as it allows customised path for each product variant, allowing the production of smaller lots and simultaneous multi-product production [9].

However, assembly line design must also consider the material handling system that ensures the most suitable material handling and transportation from one workstation to another [10]. Conveyor systems are among the most used material handling systems because of their simplicity and effectiveness, even in fully automated lines [11]. Still, conveyors represent a rigid structure scarcely compatible with matrix workstation layout [12].

In this context, production planning approaches can be helpful in overcoming the aforementioned limitations. First, the CONWIP system should work one product at a time by exploiting production paradigms like the economic lot scheduling in which the multi-product demand is satisfied by fixing the batch sizes and scheduling the batch production order [13]. Hence, it is important to investigate the impacts of production planning approaches on the system behaviour under different TH levels. In the literature, some approaches propose using a dynamic W* to adjust the TH to the overall needs [14]; however, this approach will propagate variability upstream, negatively impacting system performance.

Moreover, CONWIP is subjected to the risk of unbalancing the assembly line due to not directly controlling the WIP in each part of the system, but only its overall value. However, controlling the number of jobs in the parts of the line close to the bottlenecks can prevent extreme congestion conditions causing deadlocks.

This paper investigates the possibility of enhancing system flexibility and reconfigurability in a system that can be critical due to the use of CONWIP logic, conveyors and carousels, and the necessity of mitigating upstream and downstream variability. Discrete event simulation has been employed to evaluate the behaviour of a realistic system when different job sequencing strategies are applied. A scenario analysis is then exploited to analyse the interactions among different sequencing strategies and operational parameters of the assembly line (e.g. the identification of the W* for the CONWIP logic).

Problem description

The effectiveness of production planning actions, such as job sequencing, on system reconfigurability and flexibility depends on the system characteristics, the material handling system, and the resources that supply the raw materials to the line and move the finished products to the next production phase. This paper focuses on the effects of job sequencing on an assembly line that exploits conveyors; therefore, the main focus is on the material handling system and the short-term production planning at the workstation level.

The problem description. A part of a realistic assembly line for electric vehicle engines has been exploited as a case study. The assembly line has six manufacturing workstations (WSs) and a further WS devoted to quality checks (WSQC). Fig. 1 shows the assembly line with the loading and the unloading bays at the two line sides (pink rectangles in the figure) and the seven WSs (from WS1 to WSQC) intertwined by a fully automated material handling system based on conveyors.

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The assembly line follows a CONWIP logic; thus, there is always a fixed number of jobs within the system [8]. Hence, when a finished job leaves the system from the unloading bay, a new job is put within an empty pallet in the loading bay.

WS1 and WS3 work according to the blocking after service policy, that is, the processed job is unloaded from the machine only when one of the successive machines becomes idle (jobs in WS1 and WS3 are unloaded when one of the two machines in WS2 or the machine of WS4 become idle, respectively). At the same time, jobs processed by WS2 remain in the conveyor loop of WS2 until WS3 becomes idle, while jobs processed by WS4 and WS5 move within the conveyor loop until one of the machines of WS5 or WS6 becomes idle, respectively.

All the WSs except for WS1 are subject to random sampling for sending the just processed job to WSCQ for quality check. WS2 and WS5 have two identical machines, and each job must be worked twice within WS5.

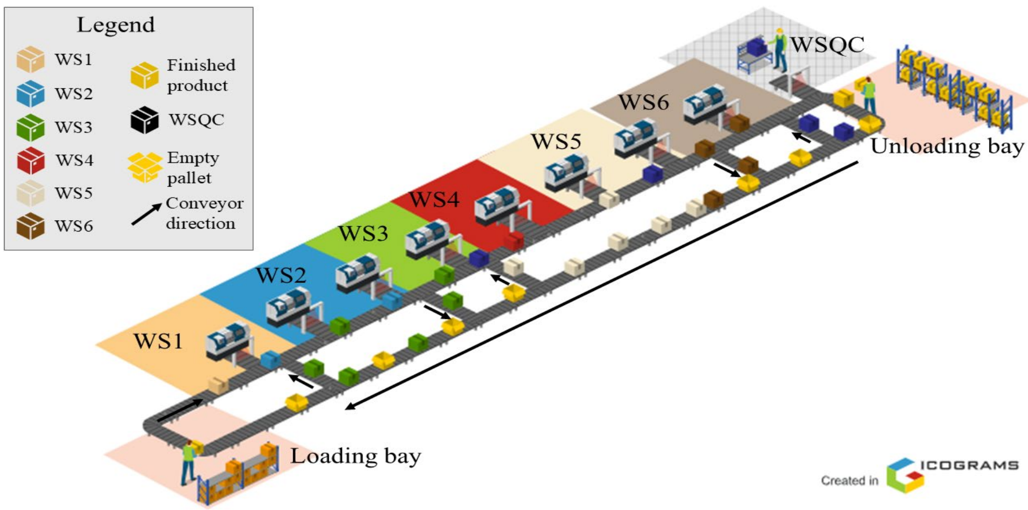

Figure 1. The assembly line has six manufacturing workstations, and the last workstation is devoted to quality checks. At the two line sides, there are the loading and unloading bays.

The proposed approach. A discrete event simulation model has been developed to simulate the system under different combinations of job sequencing rules in some WSs and different system workloads, i.e., different W*.

Some assumptions have been made to increase the experimental robustness of the results. In particular, the assembly line is balanced, i.e., all the WSs have the same processing time. WSs having two identical machines have twice the processing time of the single-machine ones; however, as WS5 has two identical machines, jobs must be processed twice, and the machine processing times are identical to the single-machine WS.

Processing times are deterministic to avoid confounding effects and focus on the variability propagation generated by the random sampling for quality check. The probability of a job being selected for quality check is 12% in each WS from 1 to 6. In the case the job is selected, it is sent to WSQC for a deterministic quality check, the duration of which is the same as the processing time of the other WSs, and then sent for rework in the origin WS.

Two job sequencing strategies have been developed: (i) a set of sequencing rules for jobs to be processed in WS5 and (ii) a set of rules for sequencing jobs waiting for the quality check in the loop of WSQC.

The two machines in WS5 follow one of the following four strategies:

- *FIFO*. First-In, First-Out strategy is the benchmark as it represents the scenario in which the jobs enter one of the two machines when they find it idle;

- *SymLWKR*. The two machines have symmetrical behaviours that prioritise the jobs with the least work remaining (LWKR). If, in the loop of WS5, there is a job that has already done one of the first operations required in WS5 (and, hence, has to be manufactured for the second time), it has higher priority than the jobs that have to be processed for the first time.
- *SymMWKR*. The two machines have symmetrical behaviours that prioritise the jobs with the most work remaining (MWKR). If, in the loop of WS5, there is a job that has done neither of the two processes required in WS5, it has higher priority than the jobs that have to be processed for the second time.
- *Asym.* The first of the two machines follows the LWKR rule, while the second follows the MWKR rule. Hence, there always is at least a machine dedicated to jobs that need to be worked for both the first and the second time.

Given a WSi (i from 1 to 6), the sequencing rules in WSQC assign priority p_i based on balancing between the number of jobs waiting to be worked in each WS (WIP_i) that have sent the jobs in the WSQC loop and their process state according to Equations (1) and (2).

$$p_i = \alpha * \frac{\sum_{i=1}^{6} WIP_i}{WIP_i} + (1-\alpha) * \frac{i}{6} \tag{1}$$

$$p_i = \alpha * \frac{\sum_{i=1}^{6} WIP_i}{WIP_i} + (1-\alpha) * \frac{1}{i} \tag{2}$$

Three values for parameter α have been used to define six job sequencing rules to assess the possible impacts of production control on inventory management:

- *FIFO*. No job sequencing is done in WSQC. It represents the benchmark;
- *Balanced incremental (B.i.*). Parameter α = 0.5 is used to give the same importance to *WIP* and *incremental* strategies by exploiting Eq. (1);
- *Balanced decremental (B.d.).*Parameter α = 0.5 is used to give the same importance to *WIP* and *decremental* strategies by exploiting Eq. (2);
- Incremental (*Inc*). Parameter α= 0 is used to apply only the *incremental* strategy Eq. (1);
- *Decremental (Dec).* Parameter α = 0 is used to apply only the *decremental* strategy, Eq (2);
- *WIP*. Parameter α = 1 is used to apply only the *WIP* strategy; Equations (1) and (2) are interchangeable.

The effectiveness of job sequencing for improving flexibility and reconfigurability is evaluated through four Key Performance Indicators (KPIs): the average shift TH, the average FT, the standard deviation of shift TH, and the occurrence of deadlocks.

The full factorial experiment has three factors: W* (ten levels), the *Scenario* indicating the sequencing strategy in WS5 (four levels), and the *WSQC Rule* indicating the sequencing strategy in WSQC (six levels). Table 1 summarises the levels of the three factors leading to 240 different scenarios.

Table 1. Experimental factors and factorial levels.

Experimental factor	Factorial levels
W*	13; 15; 17; 19; 21; 23; 25; 27; 29; 31
Scenario	*Asym*, *symLWKR*, *symMWKR*, *FIFO*
WSQC Rule	*B.d*, *B.i.*, Dec, *FIFO*, *Inc.*, *WIP*

Results

The KPIs of each one of the 240 scenarios are evaluated over 30 replications leading to 7200 experiments; each replication has a warm-up period of one year and a simulation horizon of one year. The time unit is the minute, and the daily working time is an 8-hour shift; thus, daily KPIs and shift KPIs are interchangeable.

Fig. 2 shows the impacts of the sequencing rules implemented in WS5 on the shift average TH and the average FT. Average shift TH and FT increase with W* (WIPThreshold in Fig. 2), but average shift TH increases only up to a maximum value and then decreases. In particular, Fig. 2a highlights that when implementing the *Asym* sequencing strategy, the shift average TH is slightly higher than the benchmark scenario (i.e. FIFO strategy). Conversely, the *symMWKR* sequencing strategy allows an average shift TH slightly lower than the benchmark scenario. Notably, the *symLWKR* strategy leads to a significantly lower average shift TH than the benchmark, with a TH gap from 10.86% (WIPThreshold = 13) up to 19.23% (WIPThreshold = 31).

Fig. 2b shows that only the *symLWKR* strategy is significantly different from the benchmark, increasing the flow time of a job into the system up to 19% (WIPThreshold = 31).

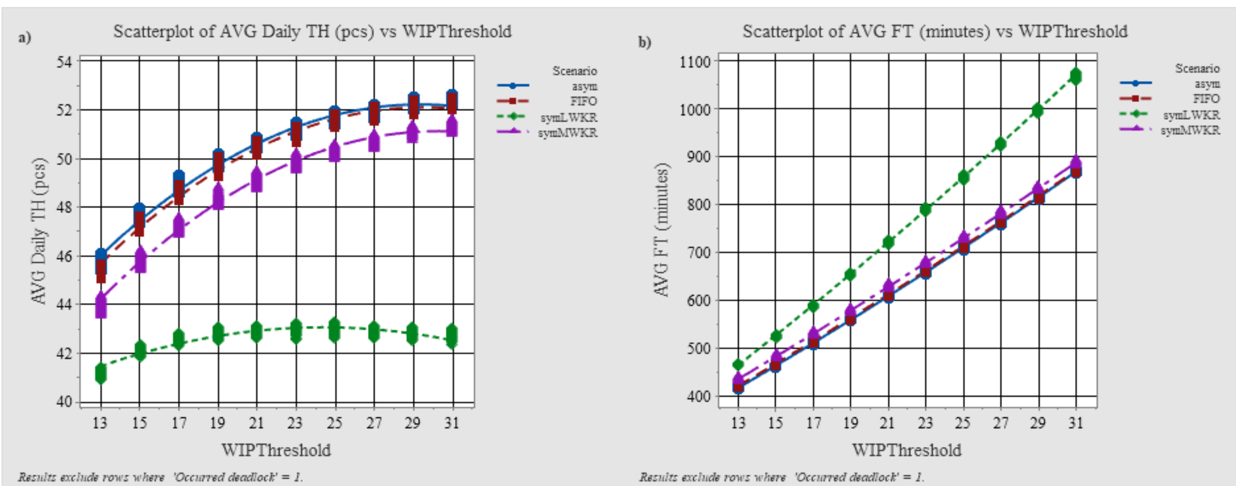

Figure 2. The impacts of the four sequencing strategies and WS5 on the average shift throughput TH (2a) and the average flowtime FT (2b) when WIPThreshold goes from 13 to 31 units.

The FT can provide insights about the reactiveness of the system by highlighting that, on average, a job stays in the system from 450 minutes (WIPThreshold = 13, almost one entire work shift) up to 900 minutes (WIPThreshold = 31, more than two working shift).

Since the job production generally spans more than one shift, the standard deviation of the average shift TH is important because highly variable average shift TH indicates scarce predictability of job completion time, upstream variability propagation to the inventory management of critical raw materials, challenges in multi-product production planning, and poor performance in reconfiguring the system for adapting to the frequent final demand fluctuations.

Fig. 3 shows the boxplots of the average shift TH standard deviation by pairwise grouping factors.

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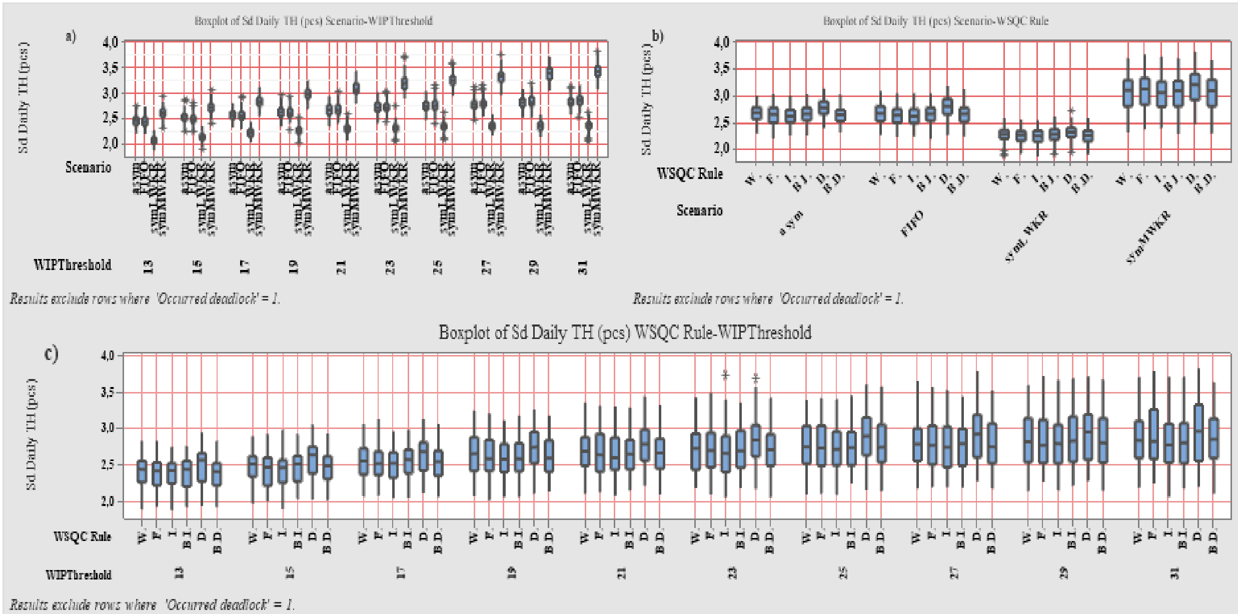

Figure 3. Boxplot of the standard deviation of average shift TH by pairwise factor grouping.

Fig. 3a highlights that the *symLKWR* strategy stabilises the variability of the average shift TH because it has a constant standard deviation that does not increase with W*. Conversely, the other sequencing strategies in WS5 have increasing standard deviation when W* increases, particularly the *symMWKR* strategy. Figures 3b and 3c show that the sequencing strategies on WSQC do not impact the standard deviation of the average shift TH (six similar boxes), but the sequencing strategies on WS5 lead to different standard deviations (Fig. 3b), which are generally increasing with W* (Fig. 3c). Note that, the analyses on standard deviations exclude all those scenarios in which a deadlock occurred (deadlock = 1) to avoid biased results. Therefore, WSQC seems marginal, but its role emerges during deadlock analysis.

The combined use of job sequencing in WS5 and WSQC is pivotal for increasing the average shift TH because the latter one increases with W*, but higher W* levels increase the deadlock probability. Fig. 4 shows the pairwise interactions of sequencing strategies on WS5, sequencing strategies on WSQC, and W* levels (*Scenario*, *WSQC Rule*, and *WIPThreshold*, respectively, in Fig. 4) impacting deadlocks that occurred over the experimentation.

Deadlocks occurred only with the WIP level equal to or greater than 27 (i.e., 27, 29, and 31). The chart in the bottom part of Fig. 4 shows that the *symLWKR* sequencing rule in WS5 is more robust to deadlock than the others, showing only one deadlock in WIPThreshold = 31 (green marker), while the benchmark (FIFO strategy) is more subjected to deadlocks than the scenarios with sequencing strategies (red line and markers are higher than the others). The two charts on the top side of Fig. 4 show that the benchmark for WSQC (*FIFO* in WSCQ) and the *Decremental* sequencing strategy prevent deadlocks (in fact, *FIFO* and *Decremental* are not in the charts of Fig. 4 because they do not have led to deadlocks). Sequencing in WSQC can reduce the probability of deadlock. Still, to minimise deadlock probability, the WSQC strategy must be selected according to the W* level and the sequencing strategy.

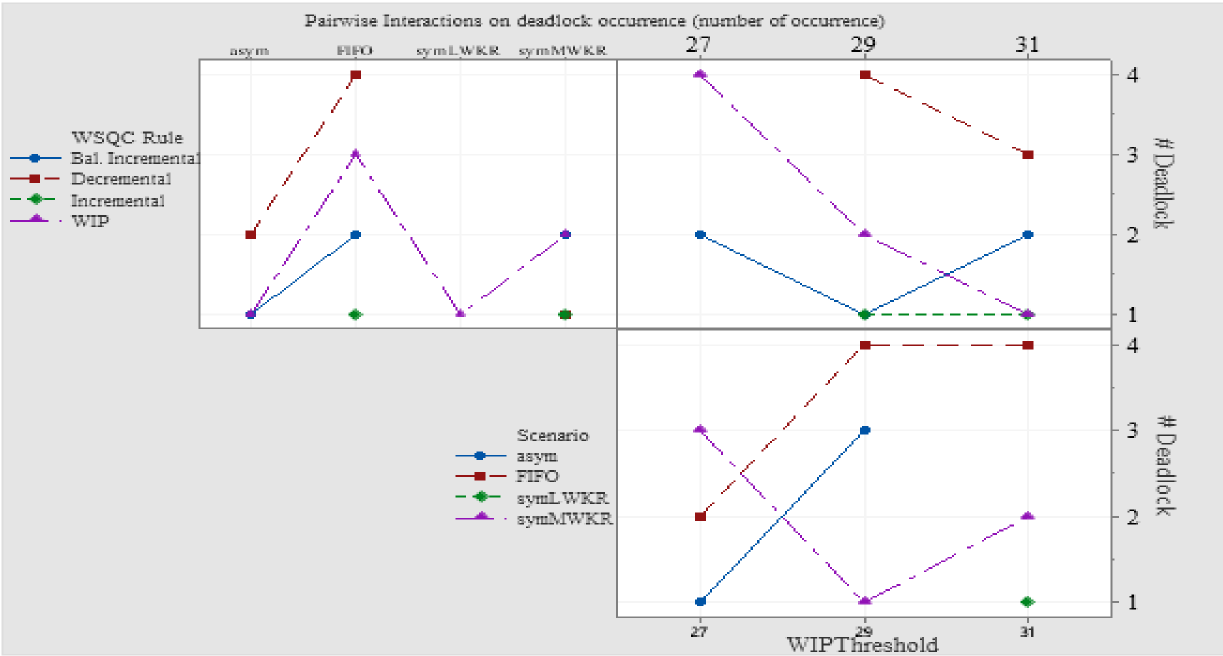

Figure 4. Pairwise interaction effects of WIPThreshold and sequencing strategies in WSQC and WS5 on the number of deadlocks that occurred during the experimentation.

Conclusion

This paper investigates the use of job sequencing in a fully automated line with workstations (WSs) connected by conveyors and controlled by a CONWIP system logic to enhance the flexibility and reconfigurability of the system. Combining sequencing rules in different WSs allows the maximisation of the average shift TH and the increase and decrease of average shift TH while reducing variability propagation. In fact, it is possible to temporarily increase or reduce the TH by combining the job sequencing rules in different manners. At the same time, it is possible to maintain a fixed consumption rate of critical raw materials by temporarily varying the critical WIP level W*.

Job sequencing WSQC can reduce the probability of deadlock, but when the sequencing rule in WS5 changes, WSQC must be adjusted. The introduction of job sequencing allows for adapting a CONWIP line, which is inherently inflexible due to the conveyor material handling system. This allows a more flexible and reconfigurable system to adjust to the product demand fluctuations, the fatigue level of the workforce, and the availability of resources moving items among the different lines or shelving while reducing the variability propagation up to the inventory management of critical raw materials.

The main limitations of this paper are that (i) the proposed approach has been investigated in a well-defined case study and (ii) the simulation approach is sensitive to the parameters used. Future research will investigate how the generalisation has to cope with the characteristics of the systems and the robustness of results. When parameters change. Moreover, the position of the WS controlling production through priority rules and the size of the conveyors and carousels are determinants for performance. Hence, future research will also investigate system design.

Finally, adaptive mechanisms will be investigated to change from one scenario to another or increase and decrease W* according to the events that impact production demand, availability and congestion of the downstream systems, and inventory management.

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