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Increasing flexibility and productivity in Industry 4.0 production networks with autonomous mobile robots and smart intralogistics

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Abstract

Manufacturing flexibility improves a firm's ability to react in timely manner to customer demands and to increase production system productivity without incurring excessive costs and expending an excessive amount of resources. The emerging technologies in the Industry 4.0 era, such as cloud operations or industrial Artificial Intelligence, allow for new flexible production systems. We develop and test an analytical model for a throughput analysis and use it to reveal the conditions under which the autonomous mobile robots (AMR)-based flexible production networks are more advantageous as compared to the traditional production lines. Using a circular loop among workstations and inter-operational buffers, our model allows congestion to be avoided by utilizing multiple crosses and analyzing both the flow and the load/unload phases. The sensitivity analysis shows that the cost of the AMRs and the number of shifts are the key factors in improving flexibility and productivity. The outcomes of this research promote a deeper understanding of the role of AMRs in Industry 4.0-based production networks and can be utilized by production planners to determine optimal configurations and the associated performance impact of the AMR-based production networks in as compared to the traditionally balanced lines. This study supports the decision-makers in how the AMR in production systems in process industry can improve manufacturing performance in terms of productivity, flexibility, and costs.

Keywords Autonomous mobile robots · Artificial Intelligence · Cloud manufacturing · Production network · Production line · Performance · Flexibility · Industry 4.0

1 Introduction

Over the past two decades, flexibility has been considered an important determinant in production system design (Das 2001; Dolgui and Proth 2010; Dubey and Ali 2014; Jain et al. 2013; Dubey et al. 2018; Ivanov et al. 2018a) and particularly Industry 4.0 has also been iden-

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tified as a major determinant in improving production flexibility (Cavalcantea et al. 2019; Dubey et al. 2019; Frank et al. 2019; Ivanov et al. 2016, 2019a, b; Ivanov and Dolgui 2019). The aspiration of Industry 4.0 is to promote the virtualization, decentralization and network building to transform the traditional production environment (Brettel et al. 2014). Thereby, the emerging technologies, such as cloud operations or industrial Artificial Intelligence, allow for new flexible production systems (Calzavara et al. 2018; Dubey et al. 2018; Panetto et al. 2019; Wamba and Akter 2019; Ivanov and Dolgui 2020). While these developments have been increasingly promoted in discrete manufacturing (Lin et al. 2019), production systems in process industries (PI) are behind in applying and exploiting the advantages of innovative technologies to improve the flexibility and productivity of their processes.

To compete in price and market shares, production lines in PI, such as dairy, ice cream or baked goods production, pharmaceutics, or detergent, rely on manufacturing systems with high productivity for a single product or small product family. The PI can be differentiated from discrete manufacturing by virtue of their high volume, low variety, dedicated and inflexible equipment, fixed routing, long changeover times, and fixed layouts (Abdulmalek et al. 2006). While discrete manufacturing has evolved from dedicated manufacturing lines to flexible manufacturing systems and reconfigurable manufacturing systems (Singh et al. 2007; Koren et al. 2018), the production systems in PI mainly rely mainly on single, dedicated production lines (Rekiek et al. 2002; Dolgui et al. 2006). Such a production line often consists of several workstations connected by conveyors leading to a production system capable of high production output rates and efficient intralogistics between workstations. These production lines are usually designed and optimized for low product variety, allowing thus little flexibility and adaptation to future trends and demands.

One difficulty in designing flexible PI production lines in the age of Industry 4.0 is a specific constellation of product mix and existing production systems. Market and industry trends favor a higher product mix and fast responsiveness to demand changes (Xu et al. 2018; Noroozi and Wikner 2017). In the past, companies in PI sold single products in standard size and packaging. Today, companies are advertising a higher variety of products and selling them in different packaging sizes. Increasing the product mix challenges the ability of these production systems to maintain high productivity. The companies either have to invest in a new production line and potentially risk low utilization or include the new product mix in existing production lines and deal with long setup times. Both alternatives inhibit the fulfilling of the productivity target.

Balanced and unbalanced, Just-In-Time (JIT), and theory of constraints have been the main approaches utilized to plan and control production lines to achieve high productivity and handle downtime and variety (Chakravorty and Atwater 1996). Alongside these approaches, lean practices, such as alignment of production with demand, elimination of waste, integration of the supplier, and the involvement of the workforce, have been of great interest to practitioners and researchers seeking to more efficiently plan and operate production systems in PI (Lyons et al. 2013). One comparative study showed that JIT lines perform best when variability in the system is low, while theory of constraints lines can deal with a higher variety of products (Chakravorty and Atwater 1996). However, PIs still lag behind discrete industries in the implementation of planning and control processes which meet their specific characteristics and needs (Dennis and Meredith 2000). Some research suggests that emerging technologies, such as cyber physical systems (Monostori et al. 2016; Panetto et al. 2019), big data (Chen et al. 2012; Wamba et al. 2015; Ivanov et al. 2019a, b; Wamba et al. 2018, 2017), Artificial Intelligence (Talbi 2016; Kusiak 2018), embedded systems (Wan et al. 2010), and smart vehicles (Qin et al. 2016), present a significant contribution to closing this gap.

Through Industry 4.0 connectivity, automation, fast information exchange and analytics, a new dimension of flexibility can be reached and new approaches to planning and controlling production systems designed. Cloud-based manufacturing is a technology which can contribute significantly to the realization of Industry 4.0 advantages (Thames and Schaefer 2016; Yin et al. 2018; Shukla et al. 2019; Ivanov and Dolgui 2020; Ivanov et al. 2016, 2018b). The aspiration of cloud manufacturing is to form production networks capable of dynamic reconfiguration and high flexibility, while intelligent big data analytics can provide global feedback to achieve high efficiency (Wang et al. 2016; Ahn et al. 2018; De Sousa Jabbour et al. 2018). Workstations and a material handling system collect and share rich process data within the cloud in real time. Information about workstation utilization and performance can support decentralization of the decision point and enable the production system to react dynamically to demand and supply changes, so that materials can be distributed according to capacity. To enable cloud manufacturing, current production systems have to be adapted. A few studies demonstrate ways to achieve these goals, with a strong emphasis on digitalizing machines and establishing IT infrastructures. Left ignored, however, was the role of material handling systems. Current literature does not specify how production systems should be adapted from a material handling perspective to enable cloud manufacturing. As a result, it is not yet clear how the flexibility and productivity of PI production systems can be increased at the shopfloor level using smart intralogistics – this is a substantive and distinctive contribution made by our study.

More specifically, our study uncovers the importance of autonomous mobile robots (AMR) in redesigning the material handling systems in the context of Industry 4.0 for the first time. We hypothesize that smart autonomous material handling systems in specific configurations with the AMR may affect PI flexibility and productivity through intralogistics in production systems in combination with cloud manufacturing. Traditional material handling equipment makes the production system rigid to change in layout and process routing. The availability of technologies using Artificial Intelligence for positioning and navigation (Fuentes-Pacheco et al. 2015; Patle et al. 2018) can support the improvements in transportation in production systems making use of intelligent vehicles, such as the AMR in order to obtain feasible solutions in increasing the flexibility and productivity of the production systems.

The objectives of this study can be formulated as research questions. First, when are the AMRs more suitable as traditional material handling equipment in PI production systems? Secondly, how can the AMR in PI production systems improve operations performance in terms of productivity, flexibility, and costs?

We contribute to literature by developing and analysing a mathematical model to investigate conditions under which it is advantageous to implement the AMR-driven flexible production networks. The sensitivity analysis highlights that the cost of AMRs and the number of shifts are the key factors in improving flexibility and productivity. The outcomes of this research can help in understanding the role of AMR in Industry 4.0-based production networks and can be utilized by decision-makers in manufacturing to determine optimal configurations and the associated performance impact of autonomous production networks in PI as compared to traditionally balanced lines. Our findings can guide firms in strategic decisions from both an economical and technical perspective regarding the installation of a new production network with an AMR system compared to continued use of existing production lines. The new analytical model developed incorporates a variety of considerations, such as estimation and comparison of the throughput of the AMR and traditional production lines in PI, their flexibility, and costs. Such a combination is unique in literature, affording more realistic application and accurate simulation of the complexities of decision-making realities.

The rest of this study is organized as follows. Section 2 reviews related literature on planning and control of production lines and systems. The corresponding models are reviewed to frame the literature gap. Section 3 is devoted to the principles of AMR. Section 4 introduces and describe s the analytical model for AMR-supported production networks using a circular loop among workstations and an inter-operational buffer. Section 5 provide s the system comparison s from an economical and technical perspective using parametrical analysis. Section 6 provides a series of sensitivity analyses and a discussion on the managerial implications of the results. The study is concluded in Section 7 with a summary of major insights and an outline of future avenues of research.

2 Literature review

Driven by the differing market requirements over the last years, manufacturing systems have faced broad changes (Yin et al. 2018), from the introduction of assembly lines to the cost-effectiveness requirements of mass production, the introduction and discussions of balanced and unbalanced lines (Davis 1965), and the establishment of JIT lines based on the "Toyota Production System" (Ono 1988), which aligns production with demand to eliminate waste. Thereby, different production line configurations, such as serial, parallel with or without crossover have been introduced. Freiheit et al. (2004) compared and analyzed the different constellations at the generic level showing the benefits in different performance dimensions, i.e., in productivity. A variety of mathematical models has been developed to support practitioners in production system design and workload optimization (Li and Meerkov 2009; Dolgui and Proth 2010; Smith 2015; Dolgui et al. 2019; Palaniappan and Jawahar 2010; Zschorn et al. 2017). An extensive review by Lusa (2008) on the complexity of decisions to be taken in designing single or parallel production lines highlights that the literature mainly discusses on how to decide upon number of lines or stations that has to be installed and on how to evaluate the performance of the production lines.

To ensure rapid market responsiveness, automated transportation systems such as conveyors, industrial vehicles, monorails, hoists, and cranes (Tompkins 2010) have been introduced in the design of new manufacturing systems. The choice of the most suitable transportation system depends on the application and boundary conditions, such as productivity, flow pattern, and flow path. For this reason, mathematical models are often used to design transportation systems. Focusing on conveyors, Andriansyah (2011) modeled an order-picking workstation to generate a certain throughput and avoid possible congestions and material queues. Concerning Rail Guided Vehicles (RGV), Calzavara et al. (2018) proposed a mathematical formulation to estimate system throughput and the right number of RGVs to employ in an automated parts-to-picker system. They report ed that system throughput does not increase linearly with the number of RGVs due to congestion phenomena. The so-called fleet sizing problem has also been assessed for Automated Guided Vehicles (AGV) and Laser Guided Vehicles (LGV). Arifin and Egbelu (2000) proposed an analytical model based on a regression analysis that provided comparable performances using simulation. Choobineh et al. (2012) proposed a model which accounts for dynamic factors in the determination of AGV fleet size. Ferrara et al. (2014) assessed the fleet sizing problem for LGV in automated warehouses, proposing an analytical model that takes into consideration stochastic phenomena and queuing implications. Reviewing the design and operational issues in AGV systems, Ganesharajah et al. (1998) highlighted that Artificial Intelligence has considerable potential to improve the state of knowledge in this area.

In general, Artificial Intelligence is a cognitive science with strong research activities in the areas of image processing, robotics, machine learning etc. (Lee et al. 2018). The developed techniques and knowledge have improved mobile robots both at the device and systems level. Techniques of Artificial Intelligence have pushed the navigation of mobile robots to autonomous driving and obstacles avoidance (Dias et al. 2018). At the system level, mobile robots are able to operate in cloud environments that can provide on-demand computing services (Xu 2012) and support in smart decision-making in the scheduling process with mobile robots (Liu et al. 2018). However, there has been a paucity of research of how the AGV technology can support improvements in productivity and flexibility of the production systems.

With recent developments in computational power and Artificial Intelligence, the indoor positioning and autonomous navigation for mobile robots have been enabled. Unlike AGVs, these vehicles are not fixed to defined guide path, but instead drive in a predefined area, allowing greater flexibility. Traditionally, an AGV system operates with a central hierarchical structure and is reductive to changes. AMRs operate autonomously, which implies decentralized decisions, such as dynamic routing and scheduling. The most common AGVs in industry are often bulky and require frequent human intervention to load and offload equipment. AMRs are often small and more agile than AGVs. This implies that AMR can access more areas and be integrated to a higher degree in workspace or workstations, enabling manufacturing flexibility and meeting the current production demands (Mosallaeipour et al. 2018). One application in the automotive sector indicates that AMRs can also be used as an assistive system, since they can interact with humans as a robotic co-workers in a wide variety of ways (Angerer et al. 2012). These advantages mean that AMRs can be introduced into production networks, increasing the flexibility of the production lines by creating connections between workstations. AMRs are particularly suited for intralogistics operations, such as transportation and part feeding inside production lines.

The majority of works in this field of research deal with scheduling to determine the best possible strategies for robot movement (Kats and Levner 2009; Ivanov et al. 2016, 2018b; Sethi et al. 1992) . Nielsen et al. (2017) assessed the implementation of AMRs in adaptive manufacturing environments, evaluating schedule modification in the mixed-integer programming (MIP) model proposed by Dang et al. (2014).

To the best of our knowledge, no study suggests methods to compare the flexibility and performance of production lines and AMR-based flexible production networks, i.e., when AMRs are a preferable solution compared to conveyors for fulfilling intralogistics tasks in a production system.

The methodology used to answer the previously introduced research questions is twofold. First, cost-profit models have been developed to assess, on a strategic level, the conditions in which AMR-supported production networks are more advantageous as compared to traditional production lines. Two throughput models for the analyzed production systems, i.e. production lines and production networks, have been adapted from the study by Freiheit et al. (2004). Based on these throughput models, a ratio has been calculated between the additional cost and the additional profit of implementing AMR-based production network system compared to the traditional production line.

Using a parametrical analysis, several scenarios have been investigated with a variable number of phases, lines, shifts, productivity, and flexibility. The results are depicted in contour maps which show the different input variables that define the range where production networks provide higher profits than production lines. Moreover, an increase in productivity and flexibility following the implementation of AMRs is evidenced.
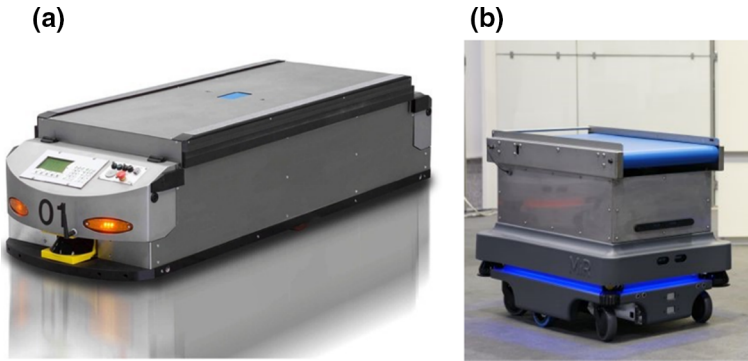
Fig. 1 **a** Traditional AGV with lifting unit, **b** AMR with conveyor top module

3 Autonomous Mobile Robots – AMR in production networks

Material handling is an essential part of material flow within a production system. To enable more flexibility in these production systems, new transportation and material handling methods have to be introduced. From a material handling perspective, conveyors, providing automatic load transfer, moving high number of items, offering high temporary buffers, and fast material transportation between workstations, have been an adequate solution (Sule 2009). Yet, these systems allow for a low degree of flexibility in routing compared to the AGVs and AMRs (Fig. 1).

The AMRs in Fig. 1 are not only small and agile, but can also provide additional services, e.g., feeding with conveyor top module. These essential attributes and capabilities allow for transportation of small containers and single units, and hence small batches between workstations. Advances in technology have facilitated the integration of AMR to a higher degree in the production systems. Traditional conveyor connections between workstations can be replaced with little effort and supplemented with simple loading and unloading stations and an AMR system. Thereby, this system is supported by Artificial Intelligence to navigate through dynamic environments and provide optimized routing. Recently, several applications of smart intralogistics systems which use such AMRs have been introduced (Scholz et al. 2016).

These changes enable the conversion of traditional, efficient production lines into flexible production networks, which distribute material to different workstations and increase the flexibility of the entire systems (see Fig. 2). Several production lines are interconnected automatically and dynamically.
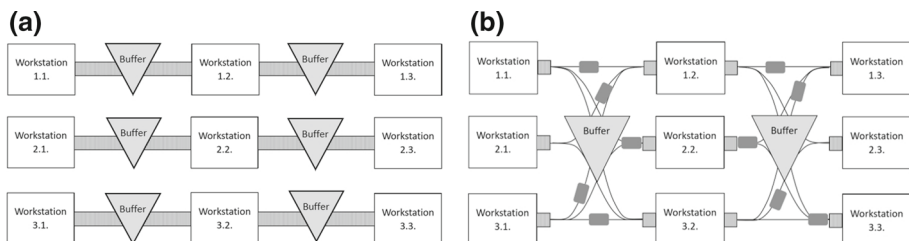

Fig. 2 **a** Traditional production systems with conveyors, **b** Production network with AMRs

AMR systems are often implemented with an inter-operational buffer, where products are temporarily stocked during changeovers, so that two consecutive production phases can be decoupled. AMR loading and unloading stations can be installed before and after workstations where grouping and singularization activities are performed. Advances in equipment can support these activities through connection to the machine or more directly by installing small conveyors on the AMRs.

4 Analytical models for the throughput calculation

In this section, we introduce the models for the throughput estimation for two production systems, i.e. production lines and production networks, based on Freiheit et al. (2004). Since the application of AMRs in PI is relatively new, the main object of this section is to adapt and describe the models that can be used at the strategic decision-making level, when aggregated and general information are available about the products, machines and material handling system, the unitary costs, and profit.

Notations

N	= number of production lines
M	= number of production phases
n	= 1…N production lines
m	= 1…M production phases
k	= number of working production lines
A_s	= availability of each machine given setup time
$A_{(s-l)}$	= availability of the entire production line given setup time
q	= productivity of each machine (pcs/h)
N_s	= number of shifts per day
H_s	= number of hours per shift per year (2000 h/year)
p	= unit profit (€/pc)
L	= length of the connecting path between two consecutive machine groups (production phase) (m)
v	= maximum speed of AMR (1 m/s)
a	= acceleration/deceleration of AMRs (1 m/s^2)
$t_{L/U}$	= loading/unloading time (5 s)
C_V	= capacity of a vehicle (10 pcs/vehicle)
c_{AMR}	= yearly unit cost of an AMR (€/year)
$c_{L/U}$	= yearly unit cost of an automated loading and unloading station (€/year)

4.1 Total throughput analysis for production lines

Consider a set of N production lines each of which contains M production phases (Fig. 3).

A limited buffer between the machines is assumed, resulting in a synchronous operation when setup occurs. This means that a typical setup lasts long enough to cause blocking or starving of the machines. Maintenance breakdowns are considered negligible. Micro-breakdowns happen in this production system (Zennaro et al. 2018), but they do not impact blocking or starving of the machines.

Following these assumptions, each line is available when all its machines are available and this affects the total throughput of the line as shown in Eq. (1):
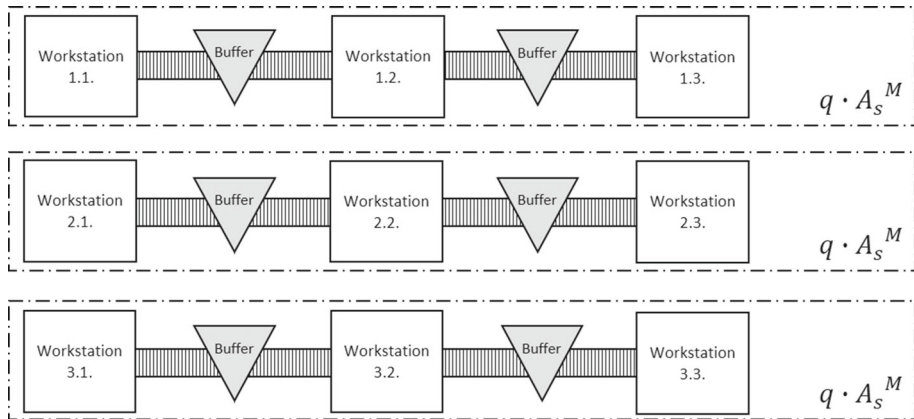
$$Q_l = q \cdot A_{s-l} = q \cdot A_s^M \tag{1}$$

Fig. 3 Total throughput for each production line with conveyors

The total throughput of the production line system can be modeled as a k-out-of-n configuration. Different scenarios occur and are characterized by the number k from 0 to N of working lines, so that the probability of each scenario is typically calculated using Eq. (2):

$$P_k^{pl} = \binom{N}{k} \cdot A_{s-l}^k \cdot (1 - A_{s-l})^{N-k} \tag{2}$$

Based on the number of working lines per scenario, the throughput of the system can be calculated as shown in Eq. (3):

$$Q_{pl} = \sum_{k=0}^{N} P_k^{pl} \cdot (Q_l \cdot k) \tag{3}$$

4.2 Total throughput analysis for AMR-based production networks

In the new production network concept, each machine of a single production phase is interconnected to the next phase through the AMR system, where the mobile robots follow a circular loop, with an inter-operational buffer located in the center of this path. In this configuration, the AMR system with the inter-operational buffer allows two consecutive production phases to be decoupled during the setup. The AMR system can also pick up and/or deliver products to all the other working machines using the buffer, so setup times do not influence the availability of other groups of machines, but only the availability of the group of machines of the production phase at which setup is occurring (Fig. 4).

This group of machines can be modeled as a k-out-of-n system, where the probability of each scenario occurring is limited to the group analyzed (Eq. 4):

$$P_k^{pn} = \binom{N}{k} \cdot A_s^k \cdot (1 - A_s)^{N-k} \tag{4}$$

Since the AMR system allows buffering and redistribution of products during setup, the throughput of the entire production network is identical in each group of machines for the production phase (Fig. 4). The total throughput can be computed as shown in Eq. (5):

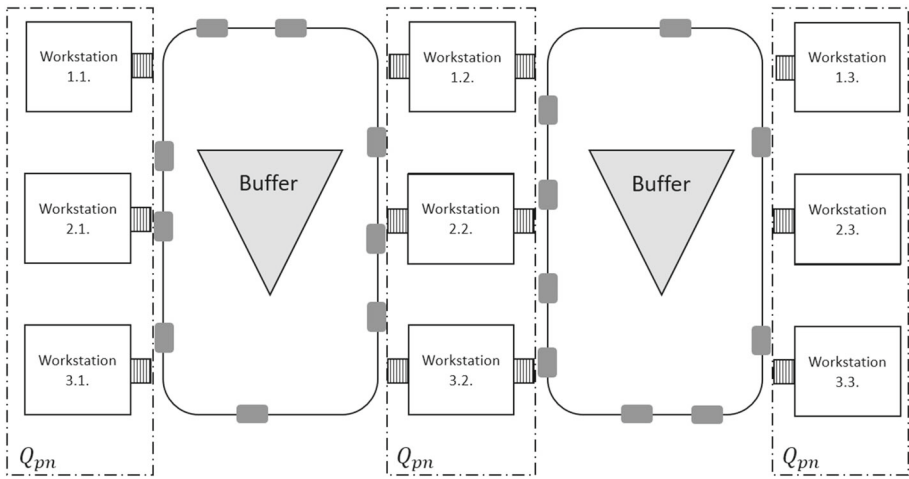$$Q_{pn} = \sum_{k=0}^{N} P_k^{pn} \cdot (q \cdot k) \tag{5}$$

Fig. 4 Total throughput for production network with AMR

The design of the AMR system in one loop can be adapted based on a procedure developed by Calzavara et al. (2018). To calculate the number of AMRs required to move all the products from one machine to another, it is necessary to know the capacity of the vehicle C_V the length of the loop path L the speed v and acceleration a of the vehicle, and the time to load and unload ($t_{L/U}$) the products.

Based on these assumptions, the throughput of each vehicle, in terms of products per hour, can be modeled as shown in Eqs. (6) and (7):

$$T_c = \frac{L}{v} + 2\frac{v}{a} + 2t_{L/U} \tag{6}$$

$$q_{AMR} = \frac{3600}{T_c} \cdot C_V \tag{7}$$

Finally, knowing that the total number of loops is $(M - 1)$ and assuming that at least two vehicles are always available in front of each machine to avoid blocking or starving, the total number of AMRs required can be computed using Eq. (8):

$$N_{AMR} = (M - 1) \cdot \left(\frac{N \cdot q}{q_{AMR}} + 4N \right) \tag{8}$$

The inter-operational buffer between consecutive phases enables the temporary stocking of products and affects the functionality of the AMR system simply by adding one loading and one unloading activity, so these can be considered negligible for the calculation of the number of required vehicles.

5 System comparison: economical and technical perspectives

An evaluation of the comparative suitability of an AMR-based production network from an economical point of view can be performed by calculating the ratio between the additional cost of implementing an AMR system and the additional profit to be gained by higher throughput.

Knowing the annual unit costs of the AMR and the annual unit costs of the loading and unloading stations needed to group and singularize products to be transported by the vehicles, the additional cost of implementing the AMR system can be defined with the help of Eq. (9):

$$\triangle TC = N_{AMR} \cdot c_{AMR} + N \cdot M \cdot c_{L/U} \tag{9}$$

The additional costs related to the inter-operational buffer, made up of a set of conveyors, is negligible, even considering those no longer in use in the production network system. The typical cost of this material handling solution for production systems in PI is a few hundred euro per linear meter. Considering that production lines can have hundreds of meters of conveyors with 7 to 10 year s amortization rates, the annual cost of this solution is several thousand euro. If gravity roller conveyors are used, the additional cost is even more negligible, since they are not motorized.

Given the average unit profit of the product p and the total number of working hours per year, based on the number of shifts N_s per day and working hours per day H_s additional profit can be formulated as follows Eq. (10):

$$\triangle TP = \left(Q_{pn} - Q_{pl}\right) \cdot p \cdot H_s \cdot N_s \tag{10}$$

The AMR-based production network system is a preferable solution compared to the traditional production line if the ratio R_{pn} is lower than 1 according to Eq. (11):

$$R_{pn} = \frac{\triangle TC}{\triangle TP} = \frac{N_{AMR} \cdot c_{AMR} + N \cdot M \cdot c_{L/U}}{\left(Q_{pn} - Q_{pl}\right) \cdot p \cdot H_s \cdot N_s} \tag{11}$$

Further, the additional throughput of the production network, resulting from greater system availability during setup, can be estimated (Eq. 12):

$$R_Q = \frac{Q_{pn}}{Q_{pl}} \tag{12}$$

Moreover, additional flexibility of the production network system, denoted as $\triangle FL$ can be estimated by setting the throughput equal to that obtained by the production lines. This is strictly correlated to the unavailability of machines by virtue of setup and changeover times (Eq. 13):

$$\triangle FL = \frac{(1 - A_s{}^{pn})}{(1 - A_{s-l})} \tag{13}$$

where $A_s{}^{pn}$ satisfies the $Q_{pn} = Q_{pl}$ (Eqs. 13, 14), where:

$$Q_{pn} = \sum_{k=1}^{N} \left[\binom{N}{k} \cdot \left(A_s{}^{pn}\right)^k \cdot \left(1 - A_s{}^{pn}\right)^{N-k} \right] \cdot (q \cdot k)$$

$$Q_{pl} = \sum_{k=1}^{N} \binom{N}{k} \cdot \left(A_s{}^{M}\right)^k \cdot \left(1 - A_s{}^{M}\right)^{N-k} \cdot \left(q \cdot A_s{}^{M} \cdot k\right) \tag{14}$$

6 Parametrical analysis and decisional maps

The two systems under consideration were compared using a parametrical analysis in order to reveal the impact of each parameter on the ratio R_{pn} Table 1 shows the values for each parameter. A total of 21,870 different scenarios were created comparing the two systems. The other parameters are considered fixed, with the values reported in the notations. The

Table 1 Parameters and values of analysis

Parameter	Unit of measurement	Values
N	-	3; 4; 5;
A_s	–	0.90; 0.92; 0.94; 0.96; 0.98;
M	–	2; 3;
q	pcs/h	1000; 5000; 10,000;
N_s	–	1; 2; 3;
L	m	50; 100; 200;
c_{AMR}	€/year	500; 1000; 5000;
$c_{L/U}$	€/year	1000; 2500; 5000;
p	€/pc	0.01; 0.1; 1;

parameters related to the vehicles (capacity, speed, acceleration/deceleration, loading and unloading times) are fixed, but the machine throughput q has been varied, providing in the same effect.

6.1 Ratio R_{pn} Analysis

As can be observed from the plot analysis (Fig. 5), the most relevant parameters for the R_{pn} are A_s, q, N_s, and c_{AMR}. The average unit profit p has a scale factor on the ratio. This means that if p is 0.1 the ratio R_{pn} is 10 times as high as when p is 0.01.

Based on these results, several decisional maps were created to understand when the application of production network system is suitable. Some parameters have been fixed, such as $p = 0.01$ €/pc, $M = 2$, $L = 100$ m, and $c_{L/U} = 2500$ €/year. Following the reasoning of that profit has a direct relation to the R_{pn} and that it is simple to adapt the analysis for different values of profit, it has been included as a constant. Further, the length of a given layout is
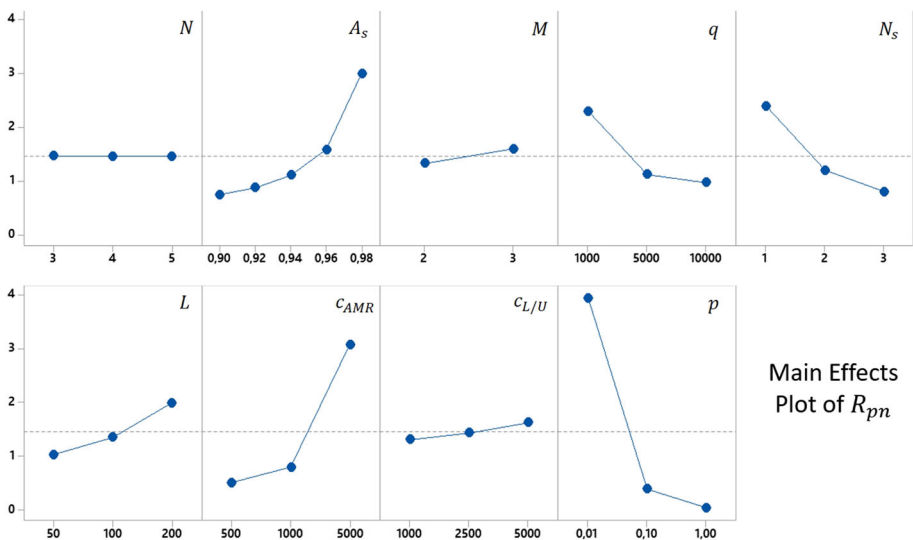

Fig. 5 Results of the main effects plot of R_{pn}

often difficult to change and can be therefore neglected, like the $c_{L/U}$ and M, since their main effect on is R_{pn} low. These graphs depict the threshold curve where $R_{pn} = 1$, varying A_s (x-axis) and q (y-axis), for different N_s and c_{AMR} (500, 1000 and 5000 €/year), such that when the size of the area to their left is greater than that on the right a production network system is more suitable and vice versa (Fig. 6).

It is interesting to observe that the production network system can be considered more suitable when the flexibility (lower availability values) and throughput required are high. The impact of the AMR cost is a relevant factor. In these analyses, it appears that the production network is suitable only when the AMR cost is 1000 €/year or less. While when it costs 5000 €/year, the production network is not suitable at all. When the AMR cost is low (c_{AMR} = 500 €/year), there is a small difference between the thresholds when the number of shifts are 2 and 3.
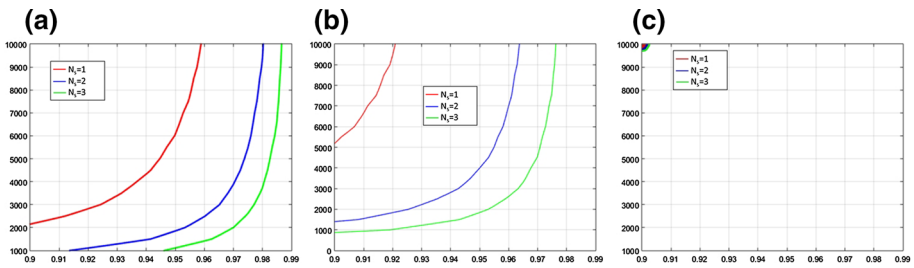
Fig. 6 Threshold curves corresponding to $R_{pm} = 1$ at different c_{AMR} values: **a** 500 € /year, **b** 1000 € /year, **c** 5000 €/year
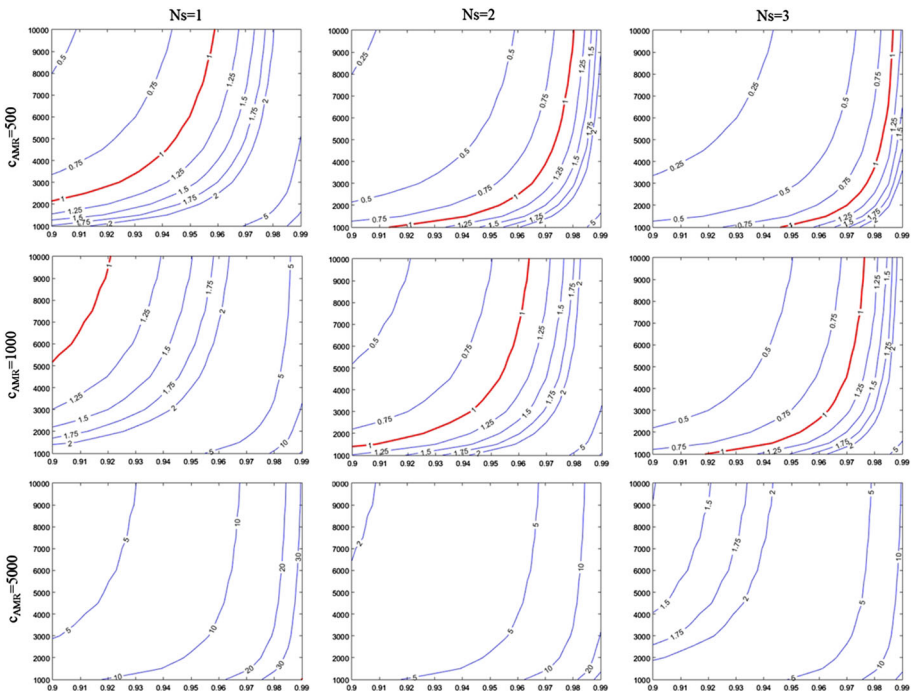

Fig. 7 Level curves for various R_{pm}

To extend the analysis to a wider range of applications, Fig. 7 depicts the level curves at different R_{pn} values, i.e., 0.25, 0.5, 0.75, 1 (red line), 1.25, 1.5, 1.75, 2, 5, 10, 20, and 30. The different level curves are calculated with profit value equal to 0.01 €/pc, and considering its linear relation with R_{pn}, they can be used to analyze cases when p has different values. For example, the level curve for $R_{pn} = 5$ when $p = 0.01$ €/pc corresponds to the level curve for $R_{pn} = 1$ when $p = 0.05$ €/pc.

Moreover, this can be also of interest for decision-makers who need to assess the sensitivity of the production line and the production network to parameters A_s and p. Considering the area where production lines are more suitable, i.e., the right side of the red curve characterized by R_{pm} values greater than 1, it is evident that the production lines are very sensitive to small changes in A_s and q, since the curves are very close to each other. On the other hand, considering the area to the left of the threshold curve (red curve) where a production network is the preferable choice, it is clear that the production network is highly robust in terms of changes in A_s and q, since the level curves are further apart.

Visualizing the different level curves, the relation and impact of the different variables of N_s, c_{AMR} and p on each other can be recognized. The graphs support to indicate which variables are beneficial to adjust to reach or increase profitability. The practitioners can use the previous graphs and equations to understand which actions to take on which factor in order to make the production network suitable, such as increase the number of shifts, or installing a cheaper AMR system, or just consider this solution for products with higher profit.

6.2 Impact of productivity and flexibility

Based on Eqs. (12) and (13), the analysis of additional throughput and flexibility depends on few parameters: the availability A_s and the number of phases M. Figures 8 and 9 show an increase in throughput R_Q and flexibility ΔFL due to the introduction of a production network and AMR system. While the increment of the throughput is higher when initial machine
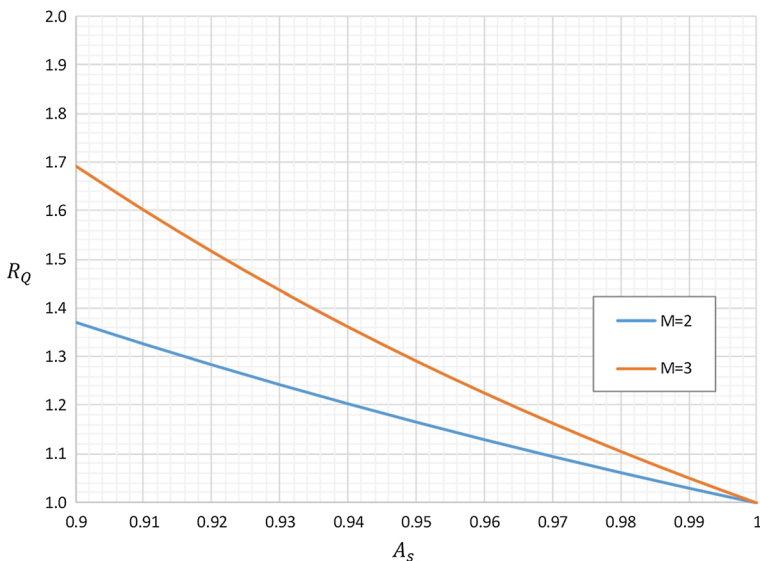

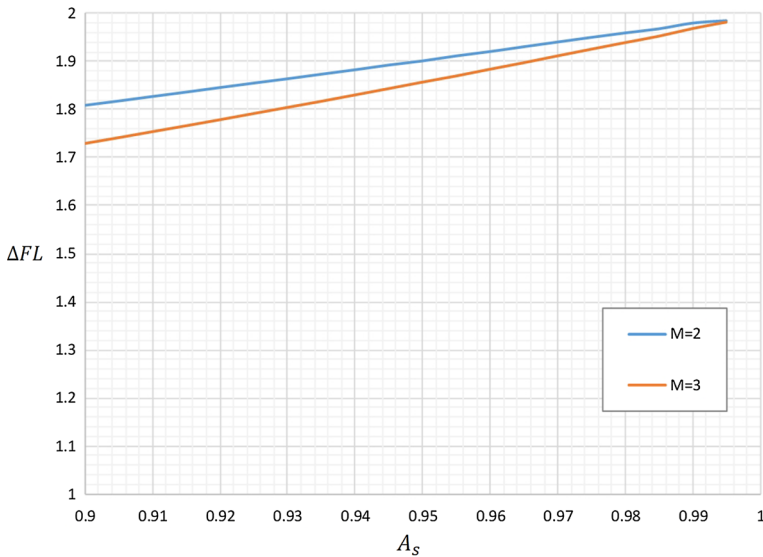**Fig. 8** Additional productivity of production network

Fig. 9 Additional flexibility of production network

availability is low, the additional flexibility gained through use of the production network system is quite constant. It is between 1.7 and 2 times more flexible than the production line. The impact of the number of phases on this increment is low.

Both the increases in throughput and the higher flexibility resulting from the introduction of the AMR system are considerable, allowing for interconnection among all the machines of the production system.

7 Conclusion

Industry 4.0 highlights the importance of building networks and decentralizing to transform the manufacturing and production landscape in to a collaborative network that balances and combine s resources (Brettel et al. 2014). To have a reactive production system, material flow has to be digitized to enable dynamic change following real-time decisions. In this study, we focused on deciphering the possibilities of an increased responsiveness in production by considering a material handling system that can adapt quickly to changes through AMR. While these developments have been increasingly promoted in discrete manufacturing in recent years, production systems in process industries are still considered behind in applying and exploiting the advantages of innovative technologies to improve process flexibility and productivity. The availability of technologies using Artificial Intelligence for positioning and navigation can support a variety of further developments in the production systems, e.g., making use of the intelligent vehicles, such as AMR to obtain feasible solution s in increasing the flexibility and productivity of the production systems. Since AMR is an emerging technology, it is necessary for practitioners and academics to investigate how it can improve performance in terms of productivity and flexibility, the costs of the production system, and how this innovative material handling system could affect intralogistics in the era of Industry 4.0.

Our study conceptualizes and models a comprehensive and unique set of parameters, which are vital to companies wishing to compare existing and Industry 4.0-based production line designs in PI. AMRs offer a suitable alternative in decentralizing material flow because of their strong on-board computational power. Decentralizing material flow can provide more flexibility for production systems. In this research, the application of an emerging technology was studied in comparison to a very traditional production system. AMRs have been introduced to dedicated production lines, which are characteristic of PI, to transform to production networks and enable high product mix capabilities and flexibility.

The main research implication of our study is the introduction of new analytical models for estimating when the AMRs are more suitable as traditional material handling equipment in PI production systems and how they improve operations performance in terms of productivity, flexibility, and costs. This study demonstrated that production networks with AMRs are suitable for meeting the increased demand for high products mixes in PI. This statement is based on the results of an analytical model and parametrical analysis. The model developed shows the latent potential to increase flexibility and productivity in industries with higher demands for product individualization and existing dedicated equipment for mass production.

For the practitioners, it is relevant to note that the increased flexibility can be achieved with the help of AMR without a complete re-design of the production lines. In particular, the introduction of the contour maps can support the practitioners in their decision-making process when AMR-based production network and traditional production systems are compared. These production lines can evolve into autonomous production networks. AMR is a suitable approach for adapting material handling systems in PI while avoiding two major inconveniences, namely high investments in new flexible production line equipment and missing product mix flexibility. AMRs can react, move, and guide the materials to the appropriate processing workstations. Productivity can therefore be kept high due to gains in flexibility.

Then, the practitioners can use the models developed in this paper and the contour maps to obtain the knowledge about which factors can make the production network profitable. Key factors relevant to the realization of the production network are the cost of AMRs and the number of shifts. The decreasing price of AMRs makes it a feasible solution for increasing flexibility and ensuring productivity. The competitive advantage of PI depends on production networks that both provide high productivity and increased flexibility for high mix production.

Several assumptions and decisions concerning the design and analysis of the model limited some aspects of the study. Predetermined AMR path s were used for simplification and only a set of balanced production lines were considered. However, the model can be extended in future studies to include different production lines, such as unbalanced ones. In such research, the required number of workstations for each production phase could be analyzed. Different constellations might also reduce the required buffer between workstations, and how different buffer sizes impact the performance of production networks could be investigated as well.

Future research can focus on how the variables previously highlighted would influence production network performance compared that of production lines in terms of productivity and flexibility at the strategic decision-making level. At the tactical and operational level, the AMR-based production network introduced can instigate new streams of research on production planning and control of AMR s and using big data analytics to achieve high er efficiency. New planning and control models are needed for production networks and decision-support systems in order to control material flows in the era of Industry 4.0.

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