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A SIMULATION BASED APPROACH FOR SUPPORTING AUTOMATED GUIDED VEHICLES (AGVs) SYSTEMS DESIGN

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ABSTRACT

Automated Guided Vehicle (AGV) logistic handling system are widely adopted when high transportation capacity and quality of service are the most important characteristics to reach. A large number of mathematical approaches have been developed in years to address AGV systems design and control. Nevertheless, proper performance estimations have to consider the peculiar aspects of the real environment in which the AGV system operates. A simple and effective approach to the stochastic features modelling is the discrete event simulation of the real system.

This paper presents a conceptual approach that lead the analyst to set up consistent simulative models to address AGV systems design and performance estimation when applications in end-of-line logistics are considered.

1 INTRODUCTION

Recent years have seen a fast-growing attention towards automation solutions able to improve efficiency in material handling and transportation. In particular, this paper deals with internal logistic systems where Automated Guided Vehicles (AGVs) provide material transport without direct human guidance. Literature proposes several studies concerning dispatching, routing and scheduling strategies for AGVs. See Vis (2006) for a comprehensive review on the design and control of AGVs. The results from these studies demonstrate that the proper integration of AGV systems into plant layout leads to significant advantages in terms of overall efficiency.

Among all the issues which might be addressed, this paper specifically focuses on assessing some key performance indicators (KPIs) to select the most convenient number of AGV Two main approaches can be adopted in order to tackle the assessing problem: the analytical approach (Mantel and Landeweerd 1995) and the simulative approach (Liu et al. 2004), (Jansen et al. 2001). Nevertheless, the assumption of deterministic input data is a limit of several models. Furthermore, the few papers considering stochastic input data simply include statistical distributions into simulative models. As an example, Prakash and Chen (1995) incorporate stochastic part arrival patterns and variable processing times into a simulation study limited to the representation of AGV system behaviour.

The contribution of our paper consists in the definition of a framework to develop a conceptual model that is able to enlarge the system boundaries under observation in order to represent not only the fleet of AGVs, but also the operative environment in which AGVs are employed. In particular, the aim is to model the system attempting to represent the actual relation existing between customer demand generation and production planning. Once the conceptual model has been defined, simulation is then used to investigate different scenarios of such a system.

The remaining part of the paper is organized as follows. Section 2 describes the problem under investigation, and Section 3 reports about the developed methodological approach. In Section 4 the application of the proposed methodology to an actual case study is then illustrated. Finally, in Section 5 concluding remarks are reported.

2 PROBLEM STATEMENT

The problem analyzed in this paper is representative of a large number of real industrial facilities that adopt AGV systems. In particular, companies working in the field of food and beverage packaging and tissue production represent principal target of these systems.

In such companies, the production shop floor is formed by a number of parallel production lines. Each line continuously produces products following a specific pattern imposed by the production management office, while at the end of each line a pallettizer unit collects products allocating them on pallets, that becomes unitary loading unit to be dispatched by the logistic system. The production pattern is set up following optimization criteria (i.e. reduction of setup times) together with respecting budget plans derived from demand forecasting. As a consequence, lines produce at a constant rate (except when they are jammed or in a setup phase), but with different production patterns that depend on scheduling optimization policies and customer demand fulfillment. The logistic system is then charged to pick up pallets coming out from lines and to manage them until their shipment. Thus, a production plant layout usually includes the following main areas:

- the end of line area (EOLA), which consists of a number of queues of pallets containing finished products at the end of each production line;
- the storage area (SA), which is composed by racks to stock pallets waiting to be transferred into the loading area;
- the loading area (LA), which is formed by a number of loading bays in which truck load is prepared by the AGV system. This load will be subsequently loaded into trucks by means of manually guided forklift vehicles.

Pallets flow generated by these production lines is very strong, thus involving a huge workload on the logistic system and implying the adoption of a significant number of forklift vehicles to assure an adequate transportation capacity. This is one of the main reason that drives toward the adoption of AGVs instead of manually guided vehicles. Given the high traffic intensity, it is clear that automated systems can work in a more coordinated manner than human driven forklifts, thus avoiding losses in performances due to troubles arising from heavy vehicles interactions. Manually guided forklifts are only used in the final truck loading phase, as it requires human skill for operating in unknown environments.

Transporting pallets directly from end of lines to loading bays is the best way to manage the production flow typical of the aforementioned systems. In this manner, pallets remain in the system for the minimum possible time, i.e. the time exclusively needed for the transportation phase, thus involving the minimum workload for the AGV system itself. Obviously this is possible if and only if, once the production of a particular kind of product is in progress, trucks charged to the shipment of the same kind of product already engaged the loading area.

This situation can happen in several cases, but there are also periods in which lines are producing some kind of products when trucks charged to their shipment are not yet present. Different reasons can drive to this situation:

- production patterns optimized for increasing lines productivity (i.e. reducing setup times) can anticipate the production of some products;
- delays in trucks arrival due to routing problems;
- internal traffic coordination and interaction problems generate fluctuations in AGVs service time. This effect can delay the completion of loads in some loading areas, thus delaying their availability for other trucks in queue.

A storage area has to be introduced in order to allows the AGV system to work even if these discrepancies happen. This area has to accommodate all of those pallets that have been produced but cannot be shipped. Obviously, the presence of the storage area implies a reduction of space that could be more profitably utilized to deploy additional production lines. Hence, the production and the AGV systems have to be designed and managed in such a way as to reduce to a bare minimum the need and the dimension of the storage area.

Thus the main issues need to be addressed in designing shop floor logistic systems are the identification of the better number of AGVs that guarantee the fulfillment of KPIs, such as the target transportation capacity together with minimizing the size of the storage area and the capacity of the end-of-line buffers. For this purpose, one of the main aspect to be tackled is the modelling of the mechanisms that are involved in the generation of production patterns and shipment arrivals.

3 METHODOLOGICAL APPROACH

The main contribution of this work to the literature consists in the development of a methodology attempting to reproduce the behaviour of the integrated production–shipment system of a generic company producing final goods and shipping them the most directly possible to its customers.

This situation can be found when the company's market is characterized by highly standardized goods (i.e. stuff such as drinks, handkerchiefs, kitchen towels, etc.) and, as a consequence, by high volumes. Thus, the company's production floor is conveniently formed by automated production lines with high throughput needing high capacity logistic systems for shipping arrangement.

Given the high production rate of the system, there is a convenience in shipping goods to the market adopting a just-in-time approach, thus avoiding the need of large storage areas. Hence, production plans are set to chase demand orders at the possible best (by integrating demand forecasts

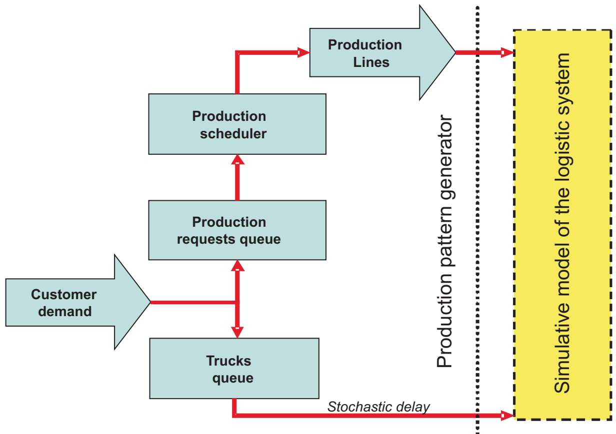

Figure 1: Conceptual model of the production pattern generator.

with orders already received). Also scheduling optimization is adopted to obtain lines production sequences aiming at reducing setup times and improving efficiency. Each short period discrepancy between production and demand is compensated by accommodating produced goods in limited storage areas located into the system, or into containers parked on the yard and waiting for the truck.

In order to support the design of such logistic systems with a simulative approach, a model able to reproduce the mechanism at the base of the production planning generation and its correlation with customers demand is necessary. Such a model must take into consideration two main aspects:

- the mean flow in the simulative model must be conservative: on a mid term base, the quantity produced for each type of good must equal the quantity of that type shipped out;
- the production pattern generation has to attempt to reproduce production plans derived from demand forecasting and line sequencing optimization.

If the first aspect did not held, whether a continuous increase on storage area utilization or an increasing waiting time on loading area would happen in the simulative model.

Figure 1 represents the block diagram of the model proposed in this paper for the generation of production patterns and shipment arrival, able to adhere to the two aforementioned aspects.

Customer demands is generated by means of a probabilistic distribution function representative of the market behaviour. As an example, a unit of demand could correspond to the load of a truck of a specified kind of good.

Once a unit of demand is generated at a generic time t, two model entities are created at the same time: a production order and a truck (under the assumption that demand unit equals truck loading capacity). On one hand, the truck is delayed of a certain amount of time Γ before enter the trucks queue at the loading bay. This amount of time can be considered as made up of a part T, representing all the deterministic components (i.e. the time needed for the line to produce demand quantity at its nominal production rate), and of a part ΔT. The component ΔT introduces stochastic fluctuations in trucks (demand) arrival time, to represent the non-perfect knowledge of the future by the production planning office. It is to point up that the intensity of this stochastic component is weighted up with respect to the intensity of demand flow, but there is not a fixed relation between the production order generated by the demand unit and its related truck introduced in the model. In deeper detail, a generic truck can load pallets produced as a consequence of a production order originally related to another truck, that, in a figurative sense, could be in late for some reasons.

On the other hand, production orders collected in the production requests queue are elaborated by the production scheduler block so as to determine production patterns for the lines. The production scheduler block has to reproduce the behaviour of mid term and short term production planning activities of the company. Hence, it has to generate production lots to be launched by attempting to aggregate production orders of the same good and scheduling them on lines taking into account changeover optimization.

This conceptual model has been applied to the case study presented in Section 4.

4 CASE STUDY

The case study deals with an actual production plant characterized by the adoption of an AGV system for material handling in a layout partitioned in the three areas explained in Section 2, i.e. EOLA, LA and SA. In particular, the EOLA presents five production line and the LA presents seven loading bays, where the loading units are stored on the ground, for further shipment. The AGVs follow a predefined path network and are subject to traffic rules in order to avoid collisions. A parking area has been included.

The methodology proposed is applied to properly model the system in order to identify the appropriate number of AGVs with respect to the following key performance indicators (KPIs):

- Mean Service Time (*Mean ST*): the mean time necessary to perform the cargo arrangement, that is the mean interval time between the arrival and departure of a truck;
- Mean EOL queue size (*Mean EOL*): the average number of items, i.e. pallets, in the EOLA;

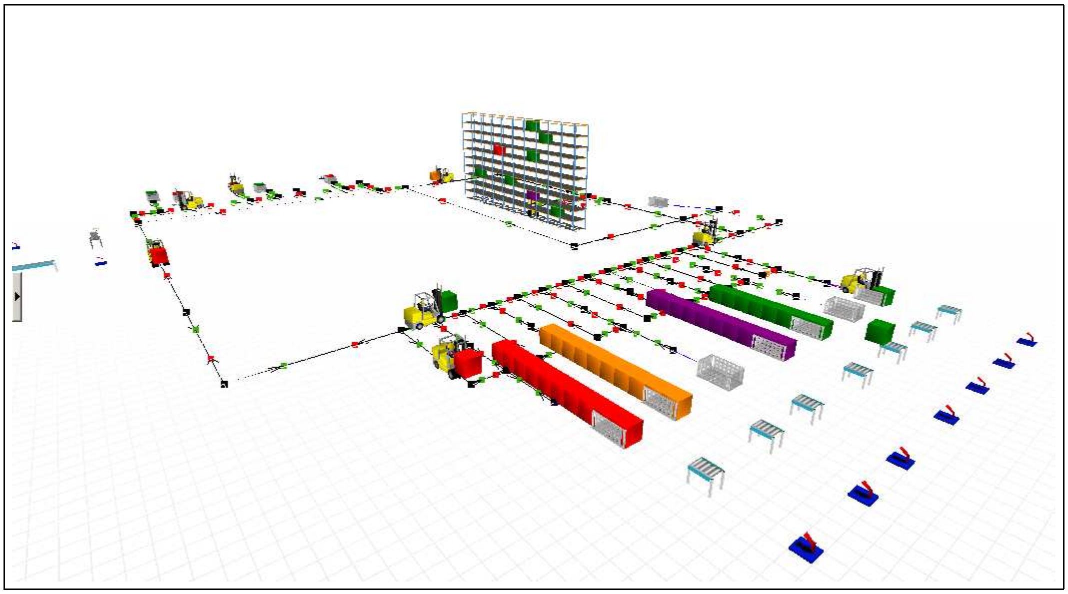

Figure 2: Simulation model.

- Maximum EOL queue size (*Max EOL*): the maximum number of items, i.e. pallets, registered in the EOLA during the planning horizon of time;
- Mean SA occupation (*Mean SA*): the average number of items, i.e. pallets, stocked in the SA.
- Maximum SA occupation (*Max SA*): the maximum number of items, i.e. pallets, registered in the SA during the planning horizon of time;

The innovative contribution consists, as explained in detail in Section 3, of expanding the system boundaries in order to include not only the shop floor, but also the generation of demand requests and the relative production patterns (i.e. the sequence of production lots).

To generate the market demand a gaussian probability function was adopted. This choice is justified by the fact that companies as the ones considered in that paper have a market characterized by a number of customers buying standardized goods, hence, demands of each good tend to assume gaussian shape. The mean value of such a gaussian distribution was set to 1 truck request each 321.3 seconds, which is the average time needed by the 5 parallel lines to produce the amount of pallets to be loaded in a truck. Product type was assigned by means of a uniform distribution, ranging from 1 to 7. The standard deviation of the demand distribution was set to 80 seconds.

The delay of truck arrival ($T+\Delta T$, as described in Section 3) was set to a triangular distribution with values $(29.2, 306.6, 642.4)$, causing the possibility to a generic truck to loose two positions at the most in the truck queue, which is managed by means of a FIFO policy.

The production orders enter the input production queue waiting to be allocated to a production line according to specific planning and scheduling rules. An example of scheduling rules is the following: since lots of different products require setups, the objective is to avoid to change product type on the same production line. Thus, in the case study the following procedure has been applied every time a production line finishes a production lot and it is necessary to choose which order within the input production queue has to be lunched:

- consider the first ten production orders in the input production queue;
- if none of the selected order has exceeded a maximum waiting time of 1200 seconds:
  - compare the kinds of products of the selected orders with the product of the last lot processed;
  - allocate to the line the first order with the same kind of product, otherwise the first order of the input production queue.

  else, allocate to the line the first order that exceeds the maximum waiting time.

In order to dimension the AGV system a simulation model (Figure 2) was built with the software tool Fleχsim$^{\text{TM}}$. Some of the objects included in the simulation model are the following:

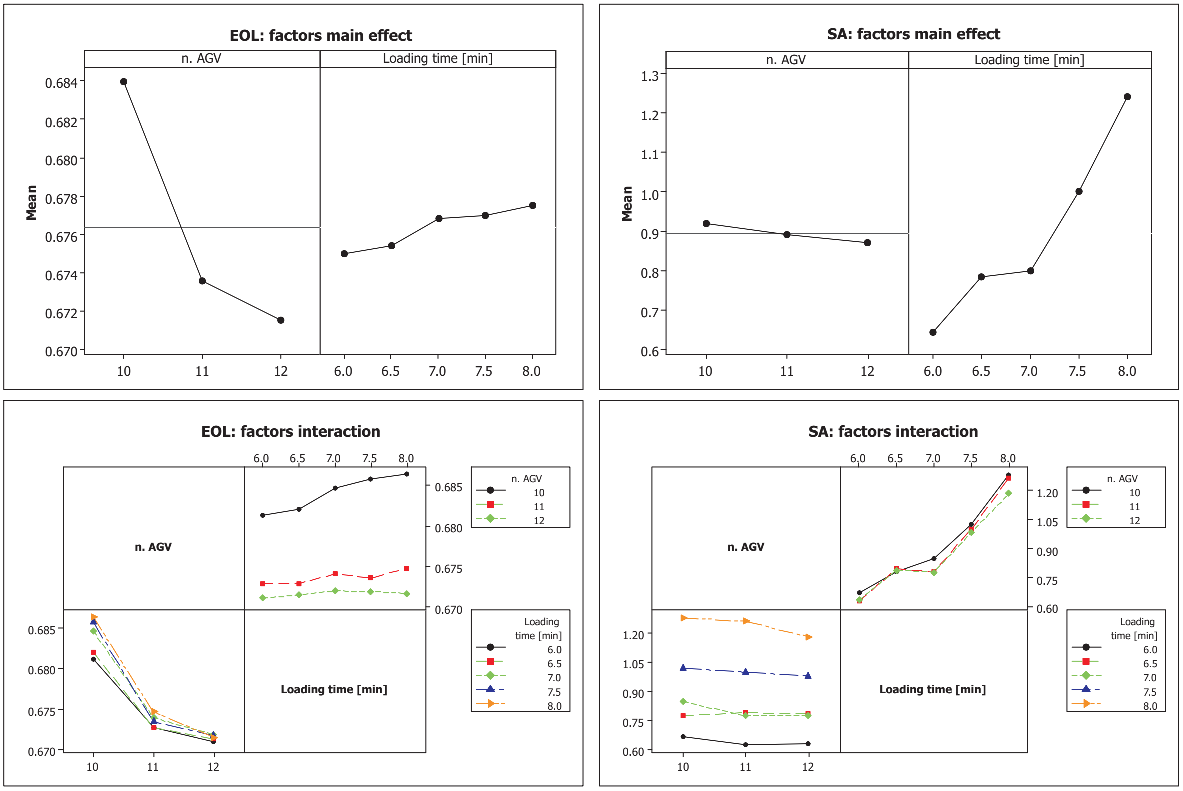

Figure 3: ANOVA results for Mean EOL and Mean SA.

- five sources from which finished products come in the model and every source is connected to a queue in the EOLA where products wait to be transported;
- seven racks in the LA where the whole charge of a shipment is collected on the ground;
- five racks in the SA to stock loading units awaiting trucks arrival;
- the path composed of network nodes connected from each other and governed by specific traffic rules to avoid collisions;
- the dwell point where AGVs park waiting a new mission;
- one dispatcher to assign an available AGV to the specific mission;
- the fleet of transporters (i.e. AGVs).

Different scenarios were tested by varying two parameters:

- the number of the available AGVs: 10, 11 and 12 AGVs were considered;
- the truck loading time, i.e. the time necessary for the manually guided forklifts to transfer the pallets arranged in the LA on the trucks: 8, 7.5, 7, 6.5 and 6 minutes were considered.

The first parameter, i.e. the number of AGVs to include in the system, represents the design variable used to optimize the system. The variation range of this factor does not include values lower than 10 AGVs cause the simulation runs executed with 9 AGVs presented instability phenomena: the system is not be able to satisfy delivery requests. On the other hand, the second parameter depends on the number and the typology of the manually guided forklifts employed. This latter variable affects the performance of the investigated system but it is not under the direct control on the part of the designer.

The simulation campaign consisted of ten model runs for each of the fifteen scenarios identified by varying the AGVs number and the truck loading time. Referring to Table 1, the first two columns identify the different scenarios, whilst the other columns report the average value of each KPI.

The ANOVA methodology was adopted to assess the effects of each investigated factor with respect to the KPIs.

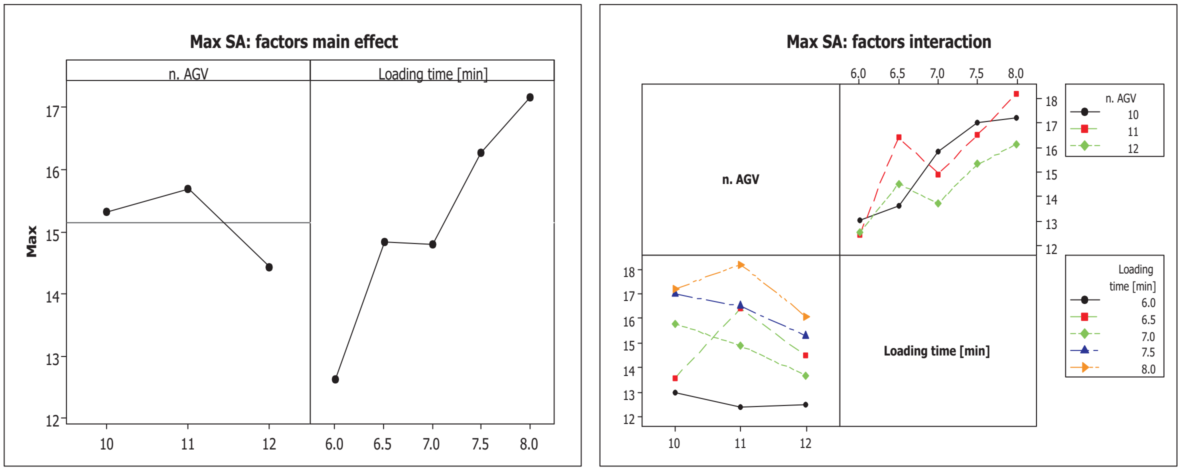

Figure 4: ANOVA results for Max SA.

Table 1: Simulation result for each scenario *(Avarage Value)*

#AGVs	Loading Time	*Mean EOL*	*Max EOL*	*Mean SA*	*Max SA*	*Mean ST*
10	8.0	0.69	2	1.28	17.20	38.14
10	7.5	0.69	2	1.02	17.00	38.27
10	7.0	0.68	2	0.85	15.80	38.36
10	6.5	0.68	2	0.78	13.60	38.32
10	6.0	0.68	2	0.67	13.00	38.35
11	8.0	0.67	2	1.26	18.20	38.15
11	7.5	0.67	2	1.00	16.50	38.24
11	7.0	0.67	2	0.78	14.90	38.47
11	6.5	0.67	2	0.79	16.40	38.35
11	6.0	0.67	2	0.63	12.40	38.39
12	8.0	0.67	2	1.18	16.10	38.19
12	7.5	0.67	2	0.98	15.30	38.31
12	7.0	0.67	2	0.78	13.70	38.41
12	6.5	0.67	2	0.79	14.50	38.36
12	6.0	0.67	2	0.64	12.50	38.39

Table 2: ANOVA results (*TLT: Truck Loading Time*)

KPI	Factor	p–Value
Mean EOL	#AGVs	< 0.05
Mean EOL	TLT	< 0.05
Mean EOL	#AGVs∗TLT	< 0.05
Mean SA	#AGVs	0.37
Mean SA	TLT	< 0.05
Mean SA	#AGVs∗TLT	0.98
Max SA	#AGVs	0.12
Max SA	TLT	< 0.05
Max SA	#AGVs∗TLT	0.63

Figure 3 and 4 shows factors influence with respect to responses. Table 2 reports statistical results: the p-values indicate that for the *Mean EOL* both the two main effects (AGVs number and truck loading time) and their interaction are significant, for both the *Mean SA* and the *Max SA* just the truck loading time is significant.

As depicted in Figure 3, the factor which mainly affects the response of the system in term of *Mean EOL* is the number of AGVs. In particular an improvement is observed by passing from 10 to 11 AGVs, while a further increase of a unit in the number of AGVs is much less relevant.

On the other side, *Mean SA* mainly depends on the truck loading time, as shown in Figure 3. The more rapidly the cargo is transferred on the truck, the more rapidly the loading bay becomes empty and available for a new cargo arrangement. Thus, the necessity to stock pallets in the SA is reduced.

Figure 4 shows that the maximum number of pallets stocked in the SA is slightly influenced by the AGVs number, whilst it is heavily affected by the truck loading time factor. The maximum number of pallets in the EOLA is equal to 2 in all the simulated scenarios. This behavior demonstrates that even 10 AGVs are sufficient to cover pallets handling requirements.

Finally, Figure 5 shows that the surface representing the mean value of the service time (*Mean ST*) is quite flat and slightly sensitive to both the number of AGVs and the

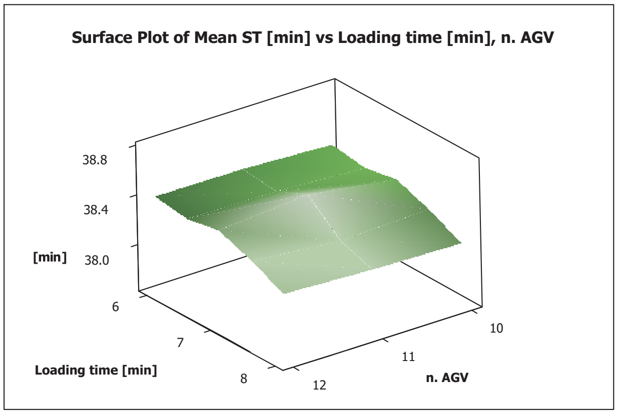

Figure 5: Mean ST surface plot.

truck loading time. This means that the AGV system does not represent a bottleneck in all the simulated scenarios. On the contrary, it is not possible to satisfy the delivery requests if only 9 AGVs are employed, as proved by a continuous increase in the number of pallets stocked in the EOLA and in the SA.

In conclusion, the simulated delivery requests can be satisfied in all the considered scenarios, demonstrating that a fleet of 10 AGVs is adequate enough to serve the whole logistic system. The number of AGVs affects significantly only one of the assessed KPIs, the *Mean EOL*, as shown in Table 2. Moreover, improvements achievable in the *Mean EOL* by increasing the number of AGVs are quite negligible: the average queue size in the EOLA is reduced only by 2% when 12 AGVs instead of 10 AGVs are adopted in the system. Thus, the choice of adopting more than 10 AGVs should not be economically justified. Another aspect to be adressed is the effect of the truck loading time on the *Max SA* parameter: as shown in Figure 4 this is the only factor that significantly affects the occupation of the SA.

5 CONCLUSIONS

In this paper a framework for the utilization of simulation tools is presented in order to analyse a logistic system where AGVs are adopted to transport finished products from the production lines to the loading area where shipment is performed. The methodological approach proposed attempts to consider in the system modelization also the stochastical aspects and variability of customer demand and production scheduling. The framework has been applied to a real logistic system and the results emerging from the case study have been presented and discussed.

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