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OPTIMIZING THE ALLOCATION OF SINGLE-LOT STOCKERS IN AN AMHS IN SEMICONDUCTOR MANUFACTURING

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ABSTRACT

This paper addresses the problem of optimally allocating single-lot stockers, also called bins, to machines in an Automated Material Handling System (AMHS) of a semiconductor wafer manufacturing facility. A Mixed Integer Linear Programming (MILP) model is proposed that assigns single-lot stockers to groups of machines performing the same types of operations. Two criteria are minimized: The maximum travel time from bins to machines and the maximum utilization of bins. An important characteristic of the problem is that the number of changes from the original allocation is limited. Computational experimental on industrial data with more than 2,000 bins and 40 machine groups are conducted. The solutions of the MILP are analyzed with regard to the trade-off between the two criteria and the impact of the allowed number of changes.

1 INTRODUCTION

Semiconductor wafer manufacturing consists of hundreds of complex operations on wafers, generally grouped in lots of 25 wafers. Operations of various processes are performed on hundreds of machines. Wafer manufacturing facilities (fabs) have re-entrant product flows, which contribute to the complexity of managing the production, transport and storage of lots. A 300mm wafer approximately travels 10 to 16 km during its processing, and typically visits more than 300 machines to undergo several hundred process steps. Efficient material handling is therefore critical and, in the most recent wafer fabs, Automated Material Handling Systems (AMHSs) are used to prevent operators from transporting excessively heavy lots.

Originally, most large AMHSs were segregated, i.e. with two types of transports: Interbay, where vehicles move lots from one process bay to another, and Intrabay, where vehicles move lots between machines in the same bay. In a segregated AMHS, some vehicles are dedicated to Interbay transports and others to Intrabay transports, and intermediate stockers are necessary to store lots that move from an interbay vehicle to an intrabay vehicle, or vice-versa. In this work, we are interested by the more recent unified AMHSs, where vehicles can transport lots from any point to any point in the fab. Our use case is the 300mm wafer fab of STMicroelectronics located in Crolles, France. A unified AMHS avoids the unnecessary storage of lots in intermediate stockers when lots are directly transferred from one machine to another. However, most lots must be stored when they have completed an operation, until a machine that can (or the machine that should) process the next operation of the lot is available. To accelerate the transfer of a lot that is stored to the machine on which it will be processed, and thus the machine to potentially be idle, single-lot stockers (called bins or Overhead Hoist Buffers, OHBs) are available in the ceiling with a very short retrieval time. However, an AMHS never has enough bins to store all lots in the Work-In-Process, and thus large stockers (that can store several hundreds lots) are also used, but with a retrieval time of a lot which is significantly larger than the retrieval time of a lot in a bin. Hence, using the bins as effectively as possible is critical. Generally, semiconductor manufacturing facilities are organized such that machines that can perform the same type of operations are assigned to the same group, and bins are assigned to machine groups. The set of bins assigned to a machine group is called its “default stocker”. Hence, when a lot must be processed on one of the machines in a group, then the AMHS tries to store it in an empty bin of the default stocker of the machine group. If all bins are occupied, i.e. the default stocker is “full”, then the lot is sent to alternate locations, which correspond to extra bins and the large stockers.

In this paper, we propose a Mixed Integer Linear Programming (MILP) model to optimize the allocation of bins to machine groups, i.e. to design the default stockers. Both the location and the number of bins in the default stockers are important, and thus two criteria are minimized. The distance from the bins in a default stocker to the machines in the corresponding group should be minimized, to quickly transport lots to machines and avoid the machines to wait and be idle. The number of bins, i.e. the size, of a default stocker is important for two reasons. An undersized default stocker will often be full, and lots will be stored in alternate locations and thus will take more time to be retrieved. On the other hand, an oversized default stocker will lead to bins being underused, and thus other default stockers to be penalized. Optimizing the allocation of bins to machine groups is complex due to the large size of instances (several thousands of bins), the variability of the Work-In-Process (WIP) and the fact that the schedule of the lots on the machines is not known beforehand. In our industrial context, the unbalance of the allocation of bins to machines groups in the AMHS can be explained by various reasons, including:

- The fact that machines in the same group are not always close to each other in the fab complicates the optimal assignment of storage locations. Indeed, when storing a lot, most often, only the next machine group in the route of the lot is known, but not precisely the machine to which the lot will later be assigned. Hence, the lots that must be processed on a machine group will be dispatched at the different locations in the fab of the machines in the group,
- And the lack of a decision support tool that automatically updates the allocation (number and location) of bins assigned to machine groups due to changes in the flows, types or quantities of products.

The paper is organized as follows. A short literature review is presented in Section 2 to position our work. The Mixed Integer Linear Program (MILP) is introduced in Section 3. Section 4 analyzes the results of computational experiments on industrial instances. Finally, some conclusions and perspectives are given in Section 5.

2 LITERATURE REVIEW

The research on Automated Material handling Systems (AMHS) mostly focuses on the layout design of the system and on the management of vehicles. Regarding the layout design, the problems tackled consist in determining the configuration of the rails, the number of vehicles (Chang et al. 2014), the positioning of the machines to be served by the vehicles, as for instance in (Ben-Salem et al. 2017) and (Ndiaye 2018). Vehicle management primarily aims at determining vehicle policies for delivering lots efficiently to machines. This issue is addressed either by studying the management of empty vehicles or the management of loaded vehicles. To manage empty vehicles, one can act on the parameters of the AMHS control system, such as the number of vehicles that should be available in bays at any time, as for example in (Chaabane et al. 2013), (Johnson 2001) and (Schmaler et al. 2017), or by proposing algorithms to find the best path to follow to deliver a lot to the right machine while avoiding traffic jams and congestion, such as in (Bartlett et al. 2014). In fact, many studies on transport and vehicle management (see e.g. (Aresi et al. 2019)) focus on optimization criteria such as minimizing machine idle times and maximizing service rate.

Large stockers are generally bottlenecks due to the required loading, unloading and internal transfer times. Most 300mm fabs have overhead single-lot stockers, which are close to the tracks and which allow shorter delivery times to machines than large stockers. However, the number of single-lot stockers is limited by the structure of the transportation system. Hence, it is not possible to store all the lots waiting to be processed in a factory in single-lot stockers. Managing the storage space is thus essential to avoid the risk of overusing some single-lot stockers and under-using others. The challenge is to best allocate the right single-lot stockers (both in terms of location and number) to the machines, since the single-lot stockers will be used to store a lot before it is transported to one of the machines on which the lot might be assigned next. Very few studies cover overhead storage issues in semiconductor manufacturing, although we can find some studies dealing with large stockers.

An efficient configuration of the storage management system is essential, and in particular the allocation of single-lot stockers to machines. Allocating single-lot stockers that are close to machines ensures short travel times and thus machines to continue processing, and allocating the right number of single-lot stockers helps to avoid lots to be redirected to a large stocker if a single-lot stocker is overused, and to prevent a single-lot stocker to be often empty if it is underused. Reducing travel times contribute to minimizing machine idle times and thus to a better machine throughput. This was showed in (Kiba et al. 2009) using simulation and different vehicle travel policies. (Jimenez et al. 2002) select the rail with the minimum travel distance between the source and destination stockers in a segregated factory to improve productivity. The productivity gain is then evaluated using discrete event simulation. (Mackulak and Savory 2001) study the impacts caused by different uses of stockers by evaluating the average delivery times on several configurations of the storage system. The results obtained by simulation show the consequences of storage on transport and production. The optimal location of stockers is studied in (Pillai et al. 1999) in several rail configurations. (Cardarelli and Pelagagge 1995) use probabilistic methods to optimize and design the storage of inter-bay systems. Their study show the difficulty to manage this problem due to the dynamics of the system and the uncertainty brought by the traffic. It also illustrates the interaction between transport, production and storage. This idea is also highlighted in (Wiethoff and Swearingen 2006), which deals with the integration of production rules in the management of stockers. Our work is in line with the work of (Dauzere-Péres et al. 2012), where the allocation of single-lot stockers to groups of machines is optimized to reduce transport times. In (Dauzere-Péres et al. 2012), a Mixed Integer Linear Programming model is proposed and tested on an industrial instance. We extend the model, and we use more industrial instances to analyze the trade-off between the two criteria that are optimized and the impact of the allowed number of changes from the original allocation.

3 MATHEMATICAL MODEL

This section presents a Mixed Integer Linear Programming (MILP) model which is an extension of the model proposed by (Dauzere-Péres et al. 2012). The differences are that we introduce a new variable modeling the waiting times to compute the sizing and that we limit the number of changes, which helps to solve the model for large instances. The model assigns bins to machine groups in a unified fab. However, changing the assignment of a bin to a machine group is time-consuming in the industrial setting, as changes must be manually done (bin per bin), which could lead to mistakes. Thus, a limit on the number of changes compared to the original situation is defined. Two criteria are minimized: (1) The maximum travel time from any bin to any machine and (2) The maximum gap between the required number of bins for each machine group (determined based on the transportation history) and the proposed number of bins.

The following parameters are needed:

- B: Number of bins,
- M: Number of machines,
- G: Number of machine groups,
- $y_{m,g} \in \{0,1\}$: Is equal to 1 if machine m is in group g, and 0 otherwise,
- $d_{i,m}$: Travel time between bin i and machine m,
- $c_{i,g} \in \{0,1\}$: Is equal to 1 if bin i is originally allocated to group g, and 0 otherwise,
- u_g: Total waiting time on the horizon (in seconds) of lots in the storage locations before being sent to a machine in group g,

- $u^{max} = \frac{\sum_{g=1}^{G} u_g}{B}$: Maximum waiting time for a machine that can be covered by a bin,
- $Nb_{changes}$: Allowed number of changes, used to limit the number of changes from the original allocation of bins.

Note that the machine groups are given in our industrial context and cannot be redefined, since each group includes the machines that can perform the same types of operations. More precisely, two machines are in the same group if they can both perform at least one operation. The lot transportation history (extracted from fab data) is used to calculate the total waiting time u_g required for machine group g, which corresponds to the sum of the waiting times of lots in single-lot stockers before being transported to machines in g. The maximum waiting time u^{max} corresponds to the sum of u_g divided by the number of bins B.

The following decision variables are used:

- $X_{i,g} \in \{0,1\}$: Is equal to 1 if bin i is assigned to machine group g, and 0 otherwise,
- TT_g: Maximum travel time (in seconds) to any machine in group g,
- $U_{i,g}$: Waiting time covered by bin i for machine group g,
- T^{max}: Maximum travel time from a bin assigned to a group to any machine in the group,
- G^{max}: Maximum gap between the required waiting time of machine group g (sum of the lot waiting times, calculated using historical data) and the waiting time associated to the proposed allocation of bins.

The Mixed Integer Linear Programming (MILP) model is formalized below:

$$\min \alpha T^{max} + G^{max} \tag{1}$$

subject to

$$\sum_{g=1}^{G} X_{i,g} = 1 \qquad \forall i = 1 \dots B \tag{2}$$

$$TT_g \geq d_{i,m} y_{m,g} X_{i,g} \qquad \forall i = 1 \dots B,\ \forall g = 1 \dots G,\ \forall m = 1 \dots M \tag{3}$$

$$T^{max} \geq TT_g \qquad \forall g = 1 \dots G \tag{4}$$

$$G^{max} \geq u_g - \sum_{i=1}^{B} U_{i,g} \qquad \forall g = 1 \dots G \tag{5}$$

$$U_{i,g} \leq u^{max} X_{i,g} \qquad \forall i = 1 \dots B,\ \forall g = 1 \dots G \tag{6}$$

$$\sum_{i=1}^{B} \sum_{g=1}^{G} c_{i,g} X_{i,g} \geq B - Nb_{changes} \tag{7}$$

$$X_{i,g} \in \{0,1\},\ U_{i,g} \geq 0 \qquad \forall i = 1 \dots B,\ \forall g = 1 \dots G \tag{8}$$

$$TT_g \geq 0 \qquad \forall g = 1 \dots G \tag{9}$$

$$T^{max},\ G^{max} \geq 0 \tag{10}$$

The objective function (1) minimizes the sum of T^{max}, corresponding to the maximum travel time (location of bins), and of G^{max}, corresponding to the maximum use of a bin (number of bins). However, T^{max} and G^{max} do not have the same order of magnitude, this is why the weight α is used to balance the two criteria. Following preliminary experiments (see also Section 4.2), it was established that $\alpha = 5,000$ balances the two criteria with the four instances. Constraints (2) ensure that each bin is assigned to one and only one machine group. Constraints (3) determine, for each machine group g, the maximum travel time from any bin assigned to g to any machine in g. Constraints (4) determine the maximum travel time for all groups. Constraints (5) determine G^{max}. Constraints (6) limit the waiting time of a bin. Constraint

(7) ensures that the number of changes is lower than the allowed number of changes. Finally, constraints (8)-(10) are the binary and the non-negativity constraints.

4 COMPUTATIONAL EXPERIMENTS

Section 4.1 details how the experiments were conducted. With a limit of 50 on the allowed number of changes compared to the original allocation, i.e. $Nb_{changes} = 50$, the trade-off between both criteria in the objective function is analyzed in Section 4.2. This limit is chosen because, in our industrial context, more allocation changes would be constraining to set up operationally simultaneously. Indeed, the software setting the parameters of the AMHS only enables to change the allocation of one bin at a time. Also, each bin priority must be updated without mistake. Thus, this requires double-checking which is time-consuming for a large number of bins. Moreover, it is important to limit the number of changes to avoid the risk of deteriorating performance indicators that are not explicitly modeled in our objective function. For instance, it is preferred not to assign bins in the same area to many different machine groups to avoid congestion. Section 4.3 discusses the impact of the allowed number of changes.

4.1 Design of Experiments

We have conducted computational experiments on industrial instances using IBM ILOG CPLEX 12.7.1 as the standard solver to solve the MILP model. The experiments were performed on a 2.7 GHz PC with 8 GB of RAM and 4 processors, with a maximum running time of one hour. Computational times were always smaller than 10 minutes when the allowed number of changes is lower than or equal to 125, i.e. $Nb_{changes} \leq 125$. However, the maximum running time was reached with $Nb_{changes} = 2138$ in the experiments of Section 4.3.

Each industrial instance includes around 600 machines aggregated in 46 machine groups, about 2,100 bins, and there are more than two weeks between the data of each instance. The distances between machines and bins, the number of processed wafers of machines and the utilization of stockers by machines are extracted from the information systems of the factory. The utilization of stockers depends on how the bins are allocated. Therefore, changing their allocation can impact their utilization and, at this stage, it cannot be predicted. Single-lot stockers used as alternate locations are not considered in the optimization because they are originally not assigned to machines. Even if alternate bins are not considered, they do not impact the study because we only focus on the deliveries on "default stockers". However, enabling the model to also assign alternate bins to default stockers is a relevant topic for future research.

4.2 Analysis of the Trade-Off between the Criteria

This section studies the balance between the two optimization criteria by changing the weight α. The following scenarios were used: $\alpha \in \{0, 500, 1250, 2000, 3000, 5000, 7500, 12000, 20000, 45000\}$ and a last scenario where only T^{max} is optimized or equivalently $\alpha \to \infty$. The numerical results can be visualized in Figure 1, where a different color is associated to each instance. Note that duplicates are deleted, the same number of experiments was carried out on each instance.

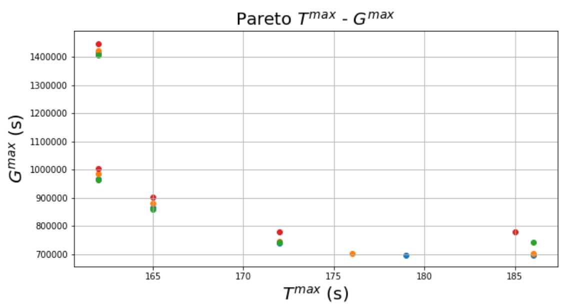

Figure 1: Balancing the two criteria

The detailed values of T^{max} and G^{max} in Figure 1 can be found in Tables 1 through 4. The MILP model does not give the same number of distinct optima for each instance when changing the values of α. This is why multiple scenarios, i.e. multiple values of α, may lead to the same optimal objective function, i.e. the same values of T^{max} and G^{max}. Hence, the value of α is only given for one scenario for each pair of optimal values of T^{max} and G^{max} in the tables.

Table 1: Instance 1, values of T^{max} and G^{max} for different values of α

	Scenarios					
	1	**2**	**3**	**4**	**5**	**6**
α	0	5 000	12 000	20 000	45 000	∞
T^{max}	186	179	172	165	162	162
G^{max}	695 170	695 170	739 475	864 251	968 231	1 411 879

Table 2: Instance 2, values of T^{max} and G^{max} for different values of α

	Scenarios					
	1	**2**	**3**	**4**	**5**	**6**
α	0	5 000	12 000	20 000	45 000	∞
T^{max}	186	176	172	165	162	162
G^{max}	703 281	703 772	744 806	881 586	984 171	1 421 867

Table 3: Instance 3, values of T^{max} and G^{max} for different values of α

	Scenarios				
	1	**2**	**3**	**4**	**5**
α	0	5 000	20 000	45 000	∞
T^{max}	186	172	165	162	162
G^{max}	742 155	742 155	859 829	963 659	1 406 668

Table 4: Instance 4, values of T^{max} and G^{max} for different values of α

	Scenarios				
	1	**2**	**3**	**4**	**5**
α	0	5 000	20 000	45 000	∞
T^{max}	185	172	165	162	162
G^{max}	778 566	778 566	902 232	1 005 312	1 445 120

The solutions of the MILP model are fairly consistent in all instances. This is partly due to the two-month instances we have considered, in which the WIP variation is limited. However, these results show that the proposed settings are stable despite the changes in transport requests to the machines. It can be observed that, even if we may have to modify the balance between the criteria in certain cases, using $\alpha = 5,000$ (second scenario in the tables) already leads to a good compromise between the criteria. Indeed, the following scenarios in Tables 1 through 4 are acceptable with a good balance between the sizing (G^{max}) and location (T^{max}) of bins:

- Instance 1: Scenarios 2, 3 and 4,
- Instance 2: Scenarios 2, 3 and 4,
- Instance 3: Scenarios 2 and 3,
- Instance 4: Scenarios 2 and 3.

From an industrial point of view, Scenarios 2 and 3 in each instance are probably the most relevant, since the time lost when a set of allocated bins is full is generally much larger than the few seconds lost in regular transport. Indeed, if the storage settings lead to short travel times to the machines in a group but the bins allocated to the group are often full, the AMHS cannot actually benefit from the short travel times because many lots will not actually be stored in the allocated single-lot stockers.

As observed in Figure 1, some instances flatten more than others. This is due to the history of the transport requests to machines, that changes the minimization of G^{max} but not of T^{max}, which on the other hand is impacted by the allowed number of changes (50 in the experiments of this section). Indeed, in the four instances, T^{max} is equal to 185 or 186 for the original allocation of bins, and the lowest value that can be obtained for T^{max} is 162. Let us now compare G^{max} for Instances 1 and 3. In Instance 3, G^{max} is equal to 1,406,668 for the original allocation of bins while, in Instance 1, it is equal to 1,411,879 and thus larger than in Instance 3. The opposite is true for the lowest value that can be obtained for G^{max}, which is equal to 742,155 in Instance 3 and 695,170 in Instance 1. Therefore, G^{max} in Instance 3 flattens more than in Instance 1.

4.3 Analysis of the Impact of the Allowed Number of Changes

This section studies how the objective function of the MILP model evolves with the allowed number of changes $Nb_{changes}$, which was varied in the following set: $\{0, 5, 10, 20, 50, 80, 100, 125, 2138\}$. The last value of 2138 actually corresponds to the case where there is no limit on the number of changes, i.e. Constraints (7) are removed from the optimization model. The results can be visualized in Figure 2, where a different color is used for each instance. The experiments were conducted with $\alpha = 5000$.

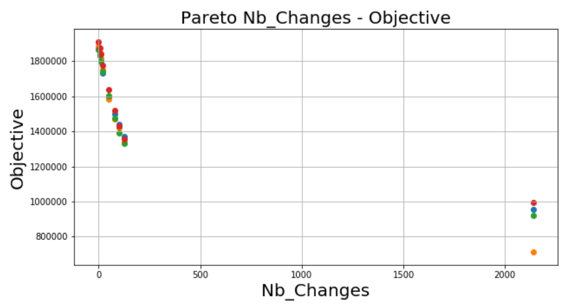

Figure 2: Evolution of objective according to number of changes

The detailed values of the objective function in Figure 2 can be found in Tables 5 through 8.

Table 5: Instance 1, objective functions for different values of allowed number of changes $Nb_{changes}$

Nb. Changes	0	5	10	20	50
Objective	1 869 913	1 835 253	1 800 593	1 731 273	1 589 120

Nb. Changes	80	100	125	2138
Objective	1 497 145	1 438 489	1 371 222	956 625

Table 6: Instance 2, objective functions for different values of allowed number of changes $Nb_{changes}$

Nb. Changes	0	5	10	20	50
Objective	1 885 760	1 851 565	1 817 370	1 748 980	1 585 272

Nb. Changes	80	100	125	2138
Objective	1 471 515	1 417 698	1 335 630	711 122

Table 7: Instance 3, objective functions for different values of allowed number of changes $Nb_{changes}$

Nb. Changes	0	5	10	20	50
Objective	1 865 331	1 830 721	1 796 111	1 739 135	1 601 405

Nb. Changes	80	100	125	2138
Objective	1 475 519	1 392 455	1 328 745	922 257

Table 8: Instance 4, objective functions for different values of allowed number of changes $Nb_{changes}$

Nb. Changes	0	5	10	20	50
Objective	1 906 933	1 872 574	1 838 214	1 775 596	1 638 616

Nb. Changes	80	100	125	2138
Objective	1 519 422	1 430 115	1 354 524	996 322

As in the previous section, the behavior of the solutions given by the MILP model are fairly consistent in all instances. The decrease of the objective function is almost linear from $Nb_{changes} = 0$ to $Nb_{changes} = 125$, although the values differ from one instance to another. This shows that, even for (almost) the same machine configuration, the changes of the Work-in-Process influence the optimal allocation of bins to machine groups. For example, the objective function for $Nb_{changes} = 80$ ranges from $1,471,515$ for Instance 2 to $1,519,422$ for Instance 4, a difference of more than 3%. Although $Nb_{changes} = 50$ is preferable in our industrial context, the results show that allowing more changes might be interesting, in particular when there are significant changes in the factory, such as new machines being added or machines being moved.

However, we believe that, if the proposed allocation changes are implemented regularly, the allowed number of changes might be reduced to less than 50, allowing for faster resolution times of the MILP model. Moreover, it could be relevant to only allow bins to be changed for a limited number of machine groups.

5 CONCLUSIONS AND PERSPECTIVES

We addressed the problem of optimizing the allocating of single-lot stockers, or bins, to machine groups in an Automated Material Handling System (AMHS) of a semiconductor wafer manufacturing facility. A Mixed Integer Linear Programming (MILP) model has been proposed with two criteria to minimize: The maximum travel time from any bin to any machine and the maximum utilization of any bin. Computational experiments were conducted on industrial instances. The compromise between the two criteria and the impact of the allowed number of allocation changes were analyzed.

Different research perspectives have been identified. A first idea we are investigating is to also consider the allocation of alternate stockers, mainly single-lot stockers not already allocated to machine groups. Another very relevant perspective is to develop a robust optimization approach to take the variations of the number of transport requests to machines into account. In the practical implementation, investigating how often the total waiting time u_g needs to be adjusted (and thus the MILP to be solved) is important, in particular to take into account changes in the product quantities and the Work-In-Process in the factory. Also, although the machine groups are given in the current industrial setting, advanced schedulers are being implemented in some work-centers, thus enabling the next machine for some lots to be known in advance. This will help to improve the assignment of bins for the corresponding machines and avoid unnecessary travel times.

REFERENCES

Aresi, L., S. Dauzère-Pérès, C. Yugma, M. Ndiaye, and L. Rullière. 2019. "AMHS Vehicle Management Policies in Semiconductor Manufacturing: A Short Review". In *2019 International Conference on Industrial Engineering and Systems Management (IESM)*, 1–6. China (Shanghai).

Bartlett, K., J. Lee, S. Ahmed, G. Nemhauser, J. Sokol, and B. Na. 2014. "Congestion-aware dynamic routing in automated material handling systems". *Computers & Industrial Engineering* 70:176–182.

Ben-Salem, A., C. Yugma, E. Troncet, and J. Pinaton. 2017. "A simulation-based approach for an effective AMHS design in a legacy semiconductor manufacturing facility". In *Proceedings of the 2017 Winter Simulation Conference (WSC)*, edited by E. H. Page, G. Wainer, V. Chan, A. D'Ambrogio, G. Zacharewicz, and N. Mustafee, 3600–3611. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Cardarelli, E., and P. M. Pelagagge. 1995. "Simulation tool for design and management optimization of automated interbay material handling and storage systems for large wafer fab". *IEEE Transactions on Semiconductor Manufacturing* 8(1):44–49.

Chaabane, A. B., S. Dauzère-Pérès, C. Yugma, L. Rullière, and G. Lamiable. 2013. "Analyzing the impact of key parameters of vehicle management policies in a unified AMHS". In *Proceedings of the 2013 Winter Simulations Conference (WSC)*, edited by R. Hill, M. Kuhl, R. Pasupathy, S.-H. Kim, and A. Tolk, 3818–3828. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Chang, K.-H., Y.-H. Huang, and S.-P. Yang. 2014. "Vehicle fleet sizing for automated material handling systems to minimize cost subject to time constraints". *IIE Transactions* 46(3):301–312.

Dauzere-Péres, S., C. Yugma, A. B. Chaabane, L. Rullière, and G. Lamiable. 2012. "A study on storage allocation in an automated semiconductor manufacturing facility". In *Proceeding of the 2012 International Material Handling Research Colloquium*.

Jimenez, J., B. Kim, J. Fowler, G. Mackulak, and Y. I. Choung. 2002. "Operational modeling and simulation of an inter-bay AMHS in semiconductor wafer fabrication". In *Proceedings of the 2002 Winter Simulation Conference (WSC)*, edited by J. L. Snowdon, J. M. Charnes, E. Yücesan, and C.-H. Chen, Volume 2, 1377–1382. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Johnson, M. E. 2001. "Modelling empty vehicle traffic in AGVS design". *International Journal of Production Research* 39(12):2615–2633.

Kiba, J.-E., G. Lamiable, S. Dauzère-Pérès, and C. Yugma. 2009. "Simulation of a full 300mm semiconductor manufacturing plant with material handling constraints". In *Proceedings of the 2009 Winter Simulation Conference (WSC)*, edited by A. Dunkin, R. Ingalls, E. Yücesan, M. Rossetti, R. Hill, and B. Johansson, 1601–1609. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Mackulak, G. T., and P. Savory. 2001. "A simulation-based experiment for comparing AMHS performance in a semiconductor fabrication facility". *IEEE transactions on semiconductor manufacturing* 14(3):273–280.

Ndiaye, M. A. 2018. "Aide à la décision pour l'optimisation d'un système automatisé complexe de transport, production et stockage.".

Pillai, D., T. Quinn, K. Kryder, and D. Charlson. 1999. "Integration of 300 mm fab layouts and material handling automation". In *1999 IEEE International Symposium on Semiconductor Manufacturing Conference Proceedings (Cat No. 99CH36314)*, 23–26.

Schmaler, R., T. Schmidt, M. Schoeps, J. Luebke, R. Hupfer, and N. Schlaus. 2017. "Simulation based evaluation of different empty vehicle management strategies with considering future transport jobs". In *Proceedings of the 2017 Winter Simulation Conference (WSC)*, edited by E. H. Page, G. Wainer, V. Chan, A. D'Ambrogio, G. Zacharewicz, and N. Mustafee, 3576–3587. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Wiethoff, T., and C. Swearingen. 2006. "AMHS software solutions to increase manufacturing system performance". In *The 17th Annual SEMI/IEEE ASMC 2006 Conference*, 306–311.

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