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SIMULATION-BASED PERFORMANCE ASSESSMENT OF SUSTAINABLE MANUFACTURING DECISIONS

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ABSTRACT

In this paper, we consider sustainable manufacturing decisions in semiconductor supply chains. A simulation-based framework is designed to assess such decisions in a dynamic and stochastic environment. Requirements for performance assessment of sustainable manufacturing decisions are derived in a first step. The architecture of the framework is then designed. We specify components that model the supplied energy and the energy consumption of the manufacturing processes. Moreover, a component for demand generation is described. A component that deals with modeling user preferences with respect to conventional and to new sustainability performance measures is also sketched. The framework is illustrated by assessing the performance of an energy-aware scheduling algorithm for batch processing machines in a rolling horizon setting.

1 INTRODUCTION

Semiconductor supply chains require sophisticated planning and control approaches due to the sheer size of the involved manufacturing facilities and the supply chains, the permanent appearance of uncertainty, and the rapid technological changes (Chien et al. 2011; Mönch et al. 2018). It is well known that a performance assessment of related planning and control approaches under dynamic and stochastic conditions is highly desirable (Mönch 2007; Ponsignon and Mönch 2014) since the behavior of a planning approach in a dynamic and stochastic setting can be fundamentally different from the observed behavior in a static and deterministic environment (Sahin et al. 2013). In addition to process uncertainty, demand uncertainty is also an important factor that has to be modeled. Discrete-event simulation provides a risk-free environment to implement rolling horizon approaches by executing the planning and control instructions in the base system, i.e. on the shop-floor level. The simulation-based performance assessment approach is extensively used in the last two decades to assess the performance of planning and scheduling approaches for wafer fabs (cf., for instance, Mönch et al. 2007 for scheduling wafer fabs; Ziarnetzky et al. 2020 for production planning in wafer fabs). The basic simulation infrastructure requires extensions if specific features of the manufacturing system at hand have to be taken into account (cf. Drießel and Mönch 2007 where automated material handling system operations are addressed in an integrated scheduling approach for wafer fabs).

Semiconductor manufacturing is energy-intensive with annual energy utility bills of $10-20 million for a single wafer fab (Mönch et al. 2018). However, sustainability issues for semiconductor supply have only recently begun to be considered in research and practice. With the emergence of such approaches, the question of their performance assessment is relevant. We argue that similar to a conventional manufacturing setting discrete-event simulation is a useful tool for performance assessment since in addition to demand and process uncertainty additional sources of uncertainty, for instance, for renewable energy such as wind or sun must be considered. In the present paper, we will therefore discuss the design of a simulation-based framework to support the performance assessment of sustainable decisions in semiconductor supply chains. The framework will be then applied within a case study for energy-aware scheduling in a wafer fab.

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The paper is organized as follows. In the next section, we describe the problem and discuss related work. The simulation framework for performance assessment of sustainable manufacturing decisions is discussed in Section 3. This includes a discussion of requirements and of architectural issues. The proposed framework is applied to assess the performance of an energy-aware batch scheduling heuristic in Section 4. Conclusions and future research directions are provided in Section 5.

2 PROBLEM SETTING

2.1 Sustainability in Semiconductor Supply Chains

Sustainable manufacturing requires the interaction of economic, environmental, and social domains (Jain and Kibira 2010; Zhou and Kuhl 2011). The economic domain includes manufacturing and financial aspects. These additional interactions compared to conventional manufacturing and supply chain management require a more sophisticated decision support and also a more elaborated performance assessment.

This is especially true for the semiconductor manufacturing domain since wafer fabs belong to the most energy-intensive manufacturing systems due to the required cleanroom conditions inside wafer fabs and the large number of highly complicated machines typical for wafer fabs (Yu et al. 2018). Semiconductor manufacturing consumes more electricity than other industries such as steel or petrochemical. Non-CO_2 greenhouse gases, for instance perfluorocarbons (PFCs), are used in wafer fabs. Since these gases have an extremely long atmospheric lifetime, it is highly desirable to reduce the PFC emission of wafer fabs (Mönch et al. 2018). Sustainability issues can be considered in principle on all planning and control levels of semiconductor supply chains. For instance, the penetration of wind, solar, and other renewable energy sources can be discussed on the strategic and tactical network design level, the reduction of CO_2 emission approaches can be studied on the tactical and operative level, while energy-aware scheduling can be considered on the operational level.

2.2 Related Work and Problem Statement

There is a large body of knowledge related to manufacturing and sustainability. Due to space limitations, we discuss only work connected to simulation-based performance assessment of sustainability strategies in manufacturing and logistics and to modeling and simulation applications in this area.

The role of discrete-event simulation for sustainable discrete manufacturing is discussed by Kibira and McLean (2008). Expected changes with respect to performance measures, data sets, simulation tools, and case studies are described. Jain and Kibira (2010) propose a system dynamics framework to evaluate sustainable decisions on the strategic level. Energy-related key performance indicators for discrete manufacturing are assessed using discrete-event simulation by Barletta et al. (2014). Discrete-event simulation is also used to support the design process of sustainable manufacturing systems (Hailala et al. 2008; Johansson et al. 2009). A simulation toolkit for sustainable operations, mainly in logistics, is described in a series of papers by Kuhl and Zhou (2009), Zhou and Kuhl (2010), and Zhou and Kuhl (2011). Special emphasis is given to the usage of performance measures that allow for assessing the environmental performance. Discrete-event simulation is also used in case studies to assess sustainable policies in different manufacturing and supply chain settings (for instance, Jaegler and Burlat 2012; Lee et al. 2012). Survey papers related to sustainable operations and simulation are provided by Thiede et al. (2013) and Moon (2016).

Sustainability issues are only rarely discussed in the semiconductor-related literature. There are only a few papers on energy conservation issues, namely Villarreal et al. (2013) and Santana-Viera et al. (2015). A design problem for a sustainable distributed power generation system for a wafer fab is discussed by Villarreal et al. (2013). Simulation-based optimization is applied to determine an appropriate number of solar photovoltaics (PVs) and wind turbines (WTs) to use renewable energy in addition to the main grid under uncertain wind speed and solar irradiance. This design problem is integrated with production planning by Ziarnetzky et al. (2017). Simulation-based optimization is used to tackle this problem. A stochastic programming model to handle contract-based demand requests received by a wafer fab owning onsite wind and solar generation units is studied by Santana-Viera et al. (2015). Chiang and Hsu (2017) consider sustainability issues in master planning for a foundry setting by incorporating carbon taxes and subsidies into a linear programming formulation. The technology–organization–environment (TOE) framework is applied by Hwang et al. (2016) to determine factors to be considered in green semiconductor supply chains, and test it using the semiconductor industry in Taiwan as a use case. Recently, energy-aware scheduling heuristics are proposed by Rocholl et al. (2020) and assessed in a static and deterministic environment.

Overall, it seems that a simulation framework that supports sustainable manufacturing on different planning and control levels is not described in the literature so far. While simulation is popular to address problems of sustainable manufacturing most of the existing work is either on a conceptual level or fairly ad-hoc. This is especially true in semiconductor manufacturing. In the present paper, we are interested in reducing this gap by enriching the simulation framework and infrastructure proposed by Mönch et al. (2007) and Ponsignon and Mönch (2014) by elements that are required for sustainable manufacturing.

3 SIMULATION FRAMEWORK FOR SUSTAINABLE MANUFACTURING DECISIONS

3.1 Requirements for the Framework

We distinguish requirements from a functional and also from a technical point of view. The following functional requirements are identified:

1. The base system, i.e. resources such as machines and operators, and the base process, i.e. system objects such as lots and the related routes have to be modeled and represented in the framework (Mönch et al. 2013). In addition to a pure conventional manufacturing setting where this is also required (cf. Ponsignon and Mönch 2014), more resources such as the main grid, grid-based distribution generation (DG) system, WTs, and PVs are required. The base system has to be considered in a broader view, i.e., parts of the manufacturing system environment also belongs to the base system. The dynamic and stochastic behavior of the base system and process have to be modeled and represented.
2. The energy consumption and the usage of specific gases caused by manufacturing processes have to be modeled.
3. The environmental consequences of the production processes, for instance, direct PFC or indirect CO_2 emissions have to be estimated.
4. External factors that impact the functions of the manufacturing process have to be modeled and represented in a time-dependent manner in the framework. This includes demand for products, but also weather conditions, and energy supply. The evolution of forecasts and other external factors must be included in the framework to correctly represent the occurrence of planning and control instances in rolling horizon approaches.
5. The planning and control processes that are applied to take into account sustainable goals have to be represented in the framework. This means especially that the approaches can be applied in a rolling horizon manner, i.e., consecutive planning and control epochs are considered.
6. Since there is always a tradeoff between financial and environmental objectives the planning and control behavior of human decision makers must be modeled and represented in the framework.

The following technical requirements have to be fulfilled:

1. The dynamic and stochastic behavior of the base system and process have to be captured by discrete-event simulation. This requires the coupling of the planning and control approaches to be assessed by a discrete-event simulation tool.
2. The different external factors and their time-dependent evolvement must be coupled with the planning and control approaches and the simulation tool.
3. Involving human decision-makers in the decision-making process require that the simulation infrastructure is able to allow for interventions by decision makers.

The different requirements are taken into account during the framework design.

3.2 Overall Architecture

The architecture is based on the principle simulation infrastructure proposed by Mönch (2007) and Ponsignon and Mönch (2014). It is shown in Figure 1. The components surrounded by grey frames belong to the principle simulation-based architecture for performance assessment of planning and control approaches. There are three additional components that are required for addressing sustainability issues. Note that we do not address interactions with the social domain. Instead of this, we mainly concentrate on modeling the interaction of the economic and environmental domains.

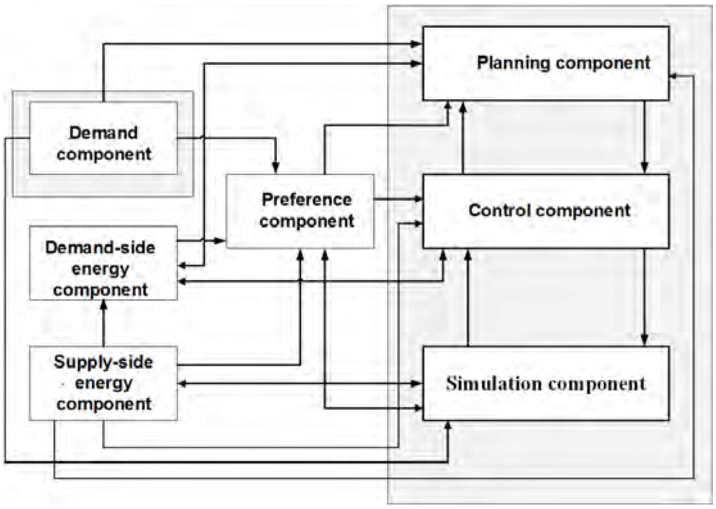

Figure 1: Component architecture of the framework.

3.3 Design of the Different Components

3.3.1 Simulation Component

This component is formed by the commercial simulation engine Autosched AP and a simulation model representing the base system and process. A blackboard-type data layer (Mönch 2007) is between the simulation model and the control component. It is located in the memory of the simulation computer. The data layer contains important business objects of the base system and process. Their status is updated in an event-driven manner using notification functions of AutoSched AP. Whenever a business object changes its status in the simulation the corresponding object of the data layer is also updated. The data layer is the base for generating problem instances taking into account the current status of the base system and process. The simulation component is also responsible for calculating the values of different performance measures. This includes measures of ecological performance.

3.3.2 Demand Component

This component implements the martingale model of forecast evolution (MMFE) proposed by Heath and Jackson (1994). The MMFE allows for generating demand that models demand correlation across products and periods for planning purposes. The MMFE with its additive and multiplicative variants is a quite general and powerful approach (Chen and Lee 2009). The MMFE requires as an input the variance covariance (VCV) matrices of the update vectors and the demand means of the different products. Demand evolution is important for implementing realistic rolling horizon schemes (Ziarnetzky et al. 2020). The demand generator can be considered as a simple forward simulation tool. Demand forecasts for planning purposes, but also demand realizations for executing planning instructions have to be provided.

3.3.3 Planning and Control Components

The planning and control components contain the algorithms used for performance assessment. Moreover, specific functions to generate problem instances taking into account feedback from the base system and process via the blackboard-type data layer and information from the demand component are included. A stop-and-go approach is used to implement rolling horizon schemes, i.e., the planning or control components solve the current problem instances and return a planning or control decision to the data layer. The data layer provides instructions to the simulation engine which are executed until the next planning instance has to be generated and solved. The planning and control components have to interact with the preference module whenever several possible instructions are available. Energy-related information, namely energy demand and supply have to be passed to the planning and control components to make sustainable planning and control decisions.

3.3.4 Demand-side Energy Component

This component determines which energy consumption is associated with a certain planning or control decision. It is far away from being trivial to estimate the energy demand of an entire wafer fab or even for a lot of a specific product (Hu and Chua 2003; Hu et al. 2010). Since the energy price often depends on the energy usage in a specific quantity at a specific time, this component is also responsible for determining the energy cost used in planning and control approaches, i.e., it is possible to implement different types of demand response programs (Albadi and El-Saadany 2008). Among them the time-of-use (TOU) electricity cost is an important price-based demand response program, i.e., the energy price depends on the period of the energy usage.

3.3.5 Supply-side Energy Component

The component deals with modeling the energy supply. An important task is the representation of renewable energy sources in the framework. This requires, for instance, modeling the uncertain wind speed and solar irradiance which are time- and location-dependent. Physical laws must be used to determine the power provided by a single WT after the wind power volatility is determined. The same can be done for the power output of solar PVs. The provided power is determined by the PV orientation, tilt angle, calendar day, solar angle, latitude, and weather conditions. We refer to Villarreal et al. (2013) for the details. In principle, this component can be considered as a simulation tool which provides power forecasts and realizations.

3.3.6 Preference Component

This component is responsible for modeling preferences of decision makers in planning and control situations with multiple, conflicting objectives. Different approaches to articulate preferences, i.e. prior, interactive, or posterior, have to be modeled and supported. Moreover, different interaction styles, for instance, choosing a set of solutions, pairwise comparison, or reference points (Shin and Ravindran 1991) must be supported by the component. It is also important to support different types or notions of convergence, i.e. convergence in a mathematical sense or only in a psychological sense when no better solutions are found.

4 APPLICATION OF THE FRAMEWORK

4.1 Static Scheduling Problem

We are interested in assessing the performance of a local scheduling approach for a group of parallel batch processing machines based on wafer fab-wide performance measures. Batch processing machines are chosen since it is well known that they influence the dynamic behavior of a wafer fab to a large extent (Mönch et al. 2013).

We start by describing the static and deterministic scheduling problem. A finite scheduling horizon of length T is divided into discrete periods of length Δ. The considered machine group consists of m

furnaces capable of processing multiple lots simultaneously in a batch. The furnaces are identical, i.e., all have the same processing speed, power consumption, and batch capacity. The latter limits the number of lots that can be assigned to a single batch. There is a total of n lots to be scheduled. All lots being processed in the same batch are started and finished at the same time. Only lots belonging to the same family can be batched together. All lots of the same family have the same processing time. The processing time of a batch is equal to the processing time of any of its lots. Lot j becomes available at $r_j \geq 0$ and has a (local) due date d_j related to the batching machine group. Furthermore, each lot has a given weight w_j describing its importance.

The two objectives to be minimized in the static problem are the total weighted tardiness (TWT) and the electricity power cost (EPC). The TWT of a schedule S is defined by

$$TWT(S) = \sum_{j=1}^{n} w_j T_j,$$

where $T_j := (C_j - d_j)^+$ is the tardiness, C_j the completion time of lot j in S and the abbreviation $\chi^+ := \max(\chi, 0)$ is used for an arbitrary real number Ç We denote the EPC value in period t by $e(t)$. Then the EPC value of a schedule S can be calculated by

$$EPC(S) := \sum_{t=1}^{T} \sum_{i=1}^{m} e(t) z_t^i,$$

where z_t^i is 1 if a batch is processed in period t on machine i in S and zero otherwise. No assumption is made regarding the preference for either one of the objectives. Instead, an a posteriori method is used to compute the set of non-dominated solutions. A schedule S is called non-dominated if no other schedule S' exists with $TWT(S') \leq TWT(S)$ and $EPC(S') \leq EPC(S)$, and at least one of the two inequalities is strict.

4.2 Concretization of the Framework for the Present Situation

Since we know that deterministic scheduling approaches can be assessed in a rolling horizon setting in a more realistic way (Mönch et al. 2011), we are interested in applying the simulation-based framework sketched in Section 3. We will discuss the tailoring of the different components in the order in which they are specified in Subsection 3.3.

4.2.1 Simulation Component

We use the MIMAC I simulation model which is publicly available under MIMAC I (2021) in a slightly modified version. In particular, the number of furnaces of the OXIDE_1 tool group is reduced, i.e., only two furnaces are considered to ensure that this tool group is the planned bottleneck of the wafer fab. A batch capacity of six lots is assumed. The first product is processed at the furnaces twice with a processing time of 253.8 minutes and 1409.4 minutes. The second product visits the furnaces once with 135.0 minutes of processing time. Consequently, three lot families are considered. Global due dates are obtained by adding a default cycle time value of 20 days, multiplied with a random factor taken from $U[0.5,1.5]$ to the release date of a lot. Here, $U[a,b]$ refers to a uniform continuous distribution over the interval $[a,b]$. Moreover, weights are randomly chosen according to $DU[1,20]$ where $DU[a,b]$ refers to a discrete uniform distribution over the set of integers $\{a,\ldots,b\}$. Machine failures are exponentially distributed. A single simulation run is 90 days long. Five independent replications of each simulation run are performed to obtain statistically significant results. The average of these five replications are reported. The small simulation horizon and the low number of replications are due to the large computational burden of the frequently applied scheduling heuristic.

Instead of showing the TWT values with respect to the global due dates and the total EPC values for the OXIDE_1 tool group, those values are divided by the number of finished lots. As the output of the wafer fab may differ depending on the scheduling decisions, we also include the weighted tardiness of unfinished lots as if they were finished at the end of the simulation. This value is divided by the number of unfinished lots and the resulting value is added to the average TWT.

4.2.2 Demand Component

Since we do not consider any specific production planning functionality, sophisticated demand schemes are obsolete. We simply use two planned bottleneck utilization (BNU) levels of 70% and 90%, respectively. There are two products in the MIMAC I model. Although real-world arrival pattern can be more sophisticated, for the sake of simplicity, exponentially distributed inter arrival times are used for both products with a mean of 5 hours for BNU=90% and 7.5 hours for BNU=70%, respectively. The simulation is initialized with a work in process (WIP) distribution obtained from long simulation runs at the requested BNU level to avoid a warm-up period for the simulation.

4.2.3 Planning and Control Components

The static scheduling problem described in Subsection 4.1 is solved by applying a non-dominated sorting genetic algorithm (NSGA II)-type heuristic, i.e., we apply the GGA-HYB heuristic proposed by Rocholl et al. (2020). It is a grouping genetic algorithm (GGA), i.e., the chromosomes are sets of batches. The first encoding scheme is based on list scheduling. A first portion of all batches is scheduled in such a way that small TWT values are the result, whereas the second portion is scheduled to obtain small EPC values. The second encoding scheme is based on the idea that idle time between consecutively scheduled batches should be inserted to account for the fact that the EPC measure is non-regular. Obviously, it is necessary to keep machines idle in intervals with high electricity prices to compute schedules with a low electricity cost. We refer to Rocholl et al. (2020) for the details of the GGA-HYB heuristic due to space limitations.

The heuristic is applied in a rolling horizon setting, i.e., it is performed at regular intervals throughout the simulation horizon. When the heuristic is called, current machine availability and lot data is derived from the simulation model and prepared to generate the problem instance for the current scheduling epoch. In particular, all time-related properties are mapped to the scheduling horizon. All lots waiting for being processed at the OXIDE_1 tool group are considered. In addition, lots currently in process at the immediate preceding step of their routes are considered with their remaining processing time as release time in the scheduling horizon. The families and processing times of the lots are derived for the static scheduling problem from their routes.

Moreover, internal due dates are computed based on global due dates of the lots using a dynamic hot factor. Therefore, we first calculate the difference from the global due date d_j^{glob} and the current time t. Let k be the process step to be performed next on the machine of the OXIDE_1 tool group, and let be q the total number of process steps to complete lot j. The processing time of step o of lot j is p_{jo}. The hot factor is then defined as

$$h_{jk} \coloneqq \left(d_j^{glob} - t\right) / \sum_{o=k}^{q} p_{jo}.$$

Local due dates are then calculated by

$$d_j^{loc} := r_{jk} + h_{jk} p_{jk},$$

where r_{jk} is the ready time of the lots at the OXIDE_1 tool group. By design, the used scheduling heuristic can only find a feasible schedule if all lots can be completed within the prescribed scheduling horizon. To ensure feasibility, it might be necessary to restrict the number of lots to be scheduled in high workload situations. Lots are preselected by a simple heuristic approach. First, all available lots are sorted by their slack values in non-decreasing order, ties are broken by the release date in non-decreasing order and then by the lot weights in non-increasing order. Batches are then formed in a first-fit manner. Subsequently, those batches are assigned to machines with a simple list scheduling algorithm. From the so formed temporary schedule, all lots assigned to batches that can be completed within the first half of the scheduling horizon are passed to the scheduling routine. All other lots are automatically postponed to the next scheduling epoch. A limitation of the workload within the scheduling horizon is necessary to preserve some degree of freedom for decisions on batch formation and intended idle times.

The execution of a schedule in the simulation model is enforced by setting explicit start times to each lot based on the start times of the batches they are assigned to in the schedule. Lots are only selected by a machine if the current time is larger than their start time and kept in a waiting state otherwise. Hence lots with the exact same starting time and family are automatically assigned to the same batch.

4.2.4 Demand-side Energy Component

A TOU tariff for 24 hours forms the base of this component. The tariff information is deterministic and remains constant over the entire simulation horizon. The demand is implicitly modeled by the utilization of the furnaces. The details of the tariff are shown in Figure 2.

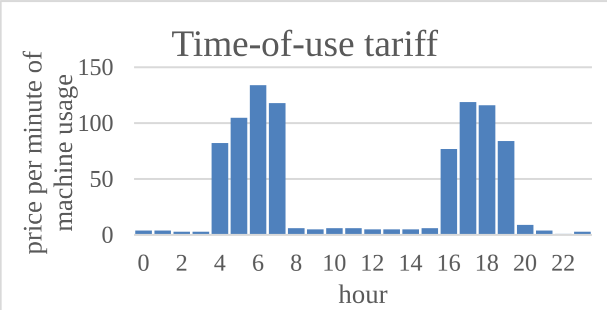

Figure 2: TOU electricity price tariff.

4.2.5 Supply-side Energy Component

This component is fairly simple in the present situation. Only an infinite power supply is assumed, i.e., shortages are not considered. The source of the supplied energy is not interesting for the purpose of the performance assessment task to be conducted.

4.2.6 Preference Component

An object of a class called decision_maker implements the preference component. The purpose of this object is choosing a single schedule from a set of non-dominated schedules provided by the control component. Therefore, properties of the set of solutions can be exploited. In addition, the object possesses a property representing its current preference for one of the objectives. The preference can change over the course of the simulation and also influences the decision. A constant preference value $\rho \in [0,1]$ is used to calculate a combined objective function value by

$$Z(S) = \rho TWT(S) + (1-\rho)EPC(S)$$

for each schedule S from the available set of non-dominated schedules. The one with the smallest $Z(S)$ is selected and executed. We perform simulation runs with preference values $\rho \in \{0.0, 0.33, 0.66, 1.0\}$.

4.2.7 Implementation Details

The different components of the simulation-based framework are coded in the C++ programming language and integrated with the simulation tool AutoSched AP 11.3 which is itself a class library written in the C++ programming language.

4.3 Design of Experiments

Every six hours of simulation time, respectively four times a day, the scheduling heuristic is performed with a prescribed computing time limit of 30 seconds of real time to find a set of non-dominated schedules. The scheduling horizon is four days with a time slot size of five minutes. The TOU tariff as shown in Figure 2 is implemented. We are interested in computing the average global TWT value and the average EPC values for the OXIDE_1 tool group depending on the BNU levels. Moreover, we look at the impact of the preference values ρ.

The results are compared against scenarios employing a simple first-in-first-out (FIFO) dispatching rule. In scenario FIFO_1, as soon as a furnace becomes available, a batch is formed with available lots of the same family by the order of their arrival at the machine group. Similarly, in the second scenario FIFO_6 lots are as well considered by the order of their arrival, but only full batches are actually started.

4.4. Simulation Results

To demonstrate that the scheduling decisions are executed correctly in the simulation, Gantt charts for a period of 14 days of the simulation employing the scheduling heuristic are depicted for different decision preferences in Figure 3. The charts show more and longer idle times for schedules with a preference set towards the EPC measure. That is because the starting of lots is postponed to less expensive periods.

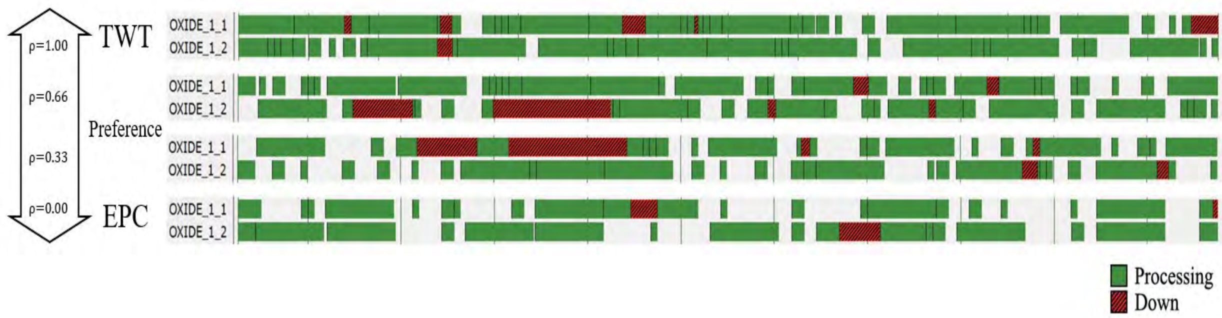

Figure 3: Visualization of the impact of preferences on machine utilization.

Table 1 shows the average fab performance for the different simulation runs in moderate and high workload situations. Generally, the formation of full batches leads to lower energy costs which can be observed from the results of FIFO_6. That is, because the energy consumption is defined on the level of batches, not lots. A preference toward the EPC minimization can further decrease the cost by around 4% in the moderate workload situation and around 8% in the high workload situation. However, such savings are accompanied by a very high increase of the TWT measure (30-357%). Only small decreases of TWT can be achieved compared to the FIFO_1 scenario, but the schedules obtained with a preference toward TWT minimization actually prove to dominate those solutions.

Table 1: Objective function values from a simulation horizon of 90 days.

Heuristic	**BNU =70%**		**BNU= 90%**	
	TWT (in min)	**EPC**	**TWT (in min)**	**EPC**
FIFO_1	141.20	13495.14	145.44	9726.06
FIFO_6	195.00	5444.24	166.31	5601.52
GGA-HYB (ρ=1.00)	140.80	10069.04	139.29	8571.80
GGA-HYB (ρ=0.66)	145.80	7587.96	152.27	6447.04
GGA-HYB (ρ=0.33)	155.00	6748.50	176.25	5637.70
GGA-HYB (ρ=0.00)	254.90	5255.20	594.47	5175.36

Schedules from a simulation run with BNU=70% are shown in Figure 4. The tradeoff between the two objectives becomes obvious as lower values for the one objective function come along with higher values of the other one. Indeed, the obtained schedules are non-dominated, all but the one found in the FIFO_1 scenario which is dominated by the solutions obtained by using the GGA-HYB heuristic with a preference of Á=1.00. It is demonstrated that scheduling decisions made locally in a rolling horizon manner can have a strong impact on the overall performance of a wafer fab. Moreover, it can be observed that always taking the extreme decision toward minimizing TWT does not only lead to a reduced TWT in this case but also shows savings regarding the EPC value compared to the FIFO_1 dispatching rule. This is caused by the fact that using the GGA-HYB schedules are chosen from the set of non-dominated schedules. Thus, in situations with locally loose internal due dates, lots can be postponed to avoid machine usage in expensive time slots. In contrast, the FIFO dispatching rule does not consider the TOU tariff at all, and there is no mechanism to arrange for intended idle times.

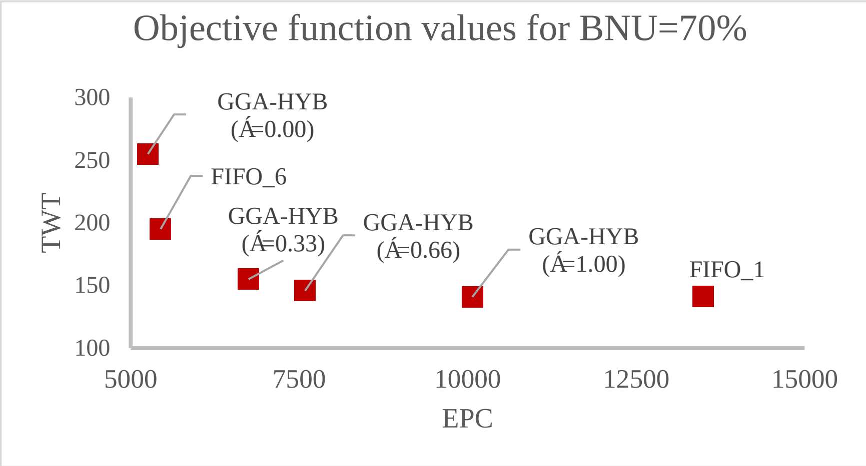

Figure 4: Schedules for BNU=70%.

5 CONCLUSIONS AND FUTURE RESEARCH

In this paper, we presented a framework for simulation-based performance assessment of sustainable manufacturing decisions in semiconductor supply chains. Requirements for the framework were discussed. We then described the main components of the framework. The application of the framework was illustrated by applying it to the performance assessment of an energy-aware scheduling heuristic for a batch processing tool group in a rolling horizon manner.

There are several directions for future research. First of all, the framework must be applied to more use cases. A natural application is the extension of the integrated planning formulations studied by Ziarnetzky et al. (2017) in a rolling horizon setting using the framework. It seems also possible to study strategic network design problems in the semiconductor domain taking into account renewable energy sources based on the proposed framework.

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REFERENCES

Albadi, M. H., and E. F. El-Saadany. 2008. "A Summary of Demand Response in Electricity Markets". *Electric Power Systems Research* 78(11):1989–1996.

Barletta, I., J. Andersson, B. Johansson, G. May, and M. Taisch 2014. "Assessing a Proposal for an Energy-based Overall Equipment Effectiveness Indicator through Discrete Event Simulation". In *Proceedings of the 2014 Winter Simulation Conference*, edited by A. Tolk, S. D. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, 1096–1107. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Chen, L., and H. Lee. 2009. “Information Sharing and Order Variability Control Under a Generalized Demand Model”. *Management Science* 55(5):781–797.

Chiang, C., and H. L. Hsu. 2017. “Incorporating Pollution Taxes and/or Subsidies into Master Planning in Semiconductor Foundry Plants”. *International Journal of Management and Sustainability* 6 (1):8–22.

Chien, C.-F., S. Dauzere-Peres, H. Ehm, J. W. Fowler, Z. Jiang, S. Krishnaswamy, L. Mönch, and R. Uzsoy. 2011. “Modeling and Analysis of Semiconductor Manufacturing in a Shrinking World: Challenges and Successes”. *European Journal of Industrial Engineering* 5(3):254-271.

Drießel, R., and L. Mönch. 2007. “Simulation Framework for Complex Manufacturing Systems with Automated Material Handling”. In *Proceedings of the 2007 Winter Simulation Conference,* edited by S. G. Henderson, B. Biller, M.-H. Hsieh, J. Shortle, J. D. Tew, and R. R. Barton, 1713-1721. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Heath, D. C., and P. L. Jackson 1994. “Modeling the Evolution of Demand Forecasts with Applications to Safety Stock Analysis in Production Distribution Systems”. *IIE Transactions* 26(3):17-30.

Heilala, J., S. Vatanen, H. Tonteri, J. Montonen, L, Salla, B. Johannson, and J. Stahre. 2008. “Simulation-based Sustainable Manufacturing System Design”. In *Proceedings of the 2008 Winter Simulation Conference*, edited by S. J. Mason, R. Hill, L. Moench, and O. Rose, 1922-1930. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Hu, S.-C., and Y. K. Chua. 2003. “Power Consumption of Semiconductor Fabs in Taiwan”. *Energy* 28:895-907.

Hu, S.-C., T. Xu, T. Chaung, and D. Y.-L. Chan. 2010. “Characterization of Energy Use in 300 mm DRAM (Dynamic Random Access Memory) Wafer Fabrication Plants (Fabs) in Taiwan”. *Energy* 35:3788-3792.

Hwang, B.-N., C.-Y. Huang, and C.-H. Wu. 2016. “A TOE Approach to Establish a Green Supply Chain Adoption Decision Model in the Semiconductor Industry”. *Sustainability* 8(2):168.

Jaegler, A., and P. Burlat. 2012. “Carbon Friendly Supply Chains: a Simulation Study of Different Scenarios”. *Production Planning and Control* 23(4): 269–278.

Jain, S., and D. Kibira. 2010. “A Framework for Multi-Resolution Modeling of Sustainable Manufacturing”. In *Proceedings of the 2010 Winter Simulation Conference*, edited by B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yücesan, 3423–3434. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Johansson, B., A. Skoogh, M. Mani, and S. Leong 2009. “Discrete Event Simulation to Generate Requirements Specification for Sustainable Manufacturing Systems Design”. In *Proceedings of the 9th Workshop on Performance Metrics for Intelligent Systems*, Gaithersburg, MD,38–42.

Kibira, D., and C. McLean. 2008. “Modeling and Simulation for Sustainable Manufacturing”. In *Proceedings of the 2nd IASTED 2008 Africa Conference on Modeling and Simulation*, September 8th – 10th, Gaborone, Botswana.

Kuhl, M. E., and X. Zhou. 2009. “Sustainability Toolkit for Simulation--Based Logistics Decisions”. In *Proceedings of the 2009 Winter Simulation Conference*, edited by M. D. Rossetti, R. R. Hill, B. Johansson, A. Dunkin, and R. G. Ingalls, 1466–1473. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Lee, J. Y., H. S. Kang, and S. D. Noh. 2012. “Simulation-based Analysis for Sustainability of Manufacturing System”. *International Journal of Precision Engineering and Manufacturing* 13(7):1221–1230.

MIMAC I. 2021. https://p2schedgen.fernuni-hagen.de/index.php?id=simulation&L=1. accessed 30th April 2021.

Mönch, L. 2007. “Simulation-Based Benchmarking of Production Control Schemes for Complex Manufacturing Systems”. *Control Engineering Practice* 15:1381-1393.

Mönch, L., J. W. Fowler, S. Dauzère-Pérès, S. J. Mason, and O. Rose. 2011. “A Survey of Problems, Solution Techniques, and Future Challenges in Scheduling Semiconductor Manufacturing Operations”. *Journal of Scheduling* 14(6):583-599.

Mönch, L., J. W. Fowler, and S. J. Mason. 2013. *Production Planning and Control for Semiconductor Wafer Fabrication Facilities: Modeling, Analysis, and Systems*. New York: Springer.

Mönch, L., R. Uzsoy, and J. W. Fowler. 2018. “A Survey of Semiconductor Supply Chain Models Part I: Semiconductor Supply Chains and Strategic Network Design”. *International Journal of Production Research* 56(13):4524-4545.

Moon, Y. B. 2016. “Simulation Modelling for Sustainability: A Review of the Literature.” *International Journal of Sustainable Engineering* 10(1): 2–19.

Ponsignon, T., and L. Mönch 2014. “Simulation-based Performance Assessment of Master Planning Approaches in Semiconductor Manufacturing”. *OMEGA* 46:21-35.

Rocholl, J., L. Mönch, and J. W. Fowler. 2020. “Bi-criteria Parallel Batch Machine Scheduling to Minimize Total Weighted Tardiness and Electricity Cost”. *Journal of Business Economics* 90:1345–1381.

Santana-Viera, V., J. Jimenez, T. Jin, and J. Espiritu. 2015. “Implementing Factory Demand Response Via Onsite Renewable Energy: A Design-of-Experiment Approach”. *International Journal of Production Research* 53(23):7034–7048.

Sahin, F., A. Narayanan, and E. P. Robinson 2013. “Rolling Horizon Planning in Supply Chains: Review, Implications and Directions for Future Research”. *International Journal of Production Research* 51(18):5413-5436.

Shin, W. S., and A. Ravindran. 1991. “Interactive Multiple Objective Optimization: Survey I - Continuous Case”. *Computers & Operations Research* 18(1):97-114.

Thiede, S., Y. Seow, J. Andersson, and B. Johansson. 2013. “Environmental Aspects in Manufacturing System Modelling and Simulation - State of the Art and Research Perspectives”. *CIRP Journal of Manufacturing Science and Technology* 6:78–87.

Villarreal, S., J. Jimenez, T. Jin, and M. Cabrera-Rios. 2013. “Designing a Sustainable and Distributed Generation System for Semiconductor Wafer Fabs”. *IEEE Transactions on Automation Science and Engineering* 10(1):16–26.

Yu, C.-M., C.-F. Chien, and C.-J. Kuo. 2017. “Exploit the Value of Production Data to Discover Opportunities for Saving Power Consumption of Production Tools”. *IEEE Transactions of Semiconductor Manufacturing* 30(4):345-350.

Zhou, X., and M. E. Kuhl. 2010. “Design and Development of a Sustainability Toolkit for Simulation”. In *Proceedings of the 2010 Winter Simulation Conference*, edited by B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yücesan, 1601–1612. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.
Zhou, X., and M. E. Kuhl. 2011. “A Sustainability Toolkit for Simulation: Recent Developments and Future Capabilities”. In *Proceedings of the 2011 Winter Simulation Conference*, edited by S. Jain, R.R. Creasey, J. Himmelspach, K.P. White, and M. Fu, 850–858. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.
Ziarnetzky, T., L. Mönch, T. Kannaian, and J. Jiménez. 2017. “Incorporating Elements of a Sustainable and Distributed Generation System into a Production Planning Model for a Wafer Fab”. In *Proceedings of the 2017 Winter Simulation Conference,* edited by W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer, and E. Page, 3519-3530. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.
Ziarnetzky, T., L. Mönch, and R. Uzsoy. 2020. “Simulation-Based Performance Assessment of Production Planning Models With Safety Stock and Forecast Evolution in Semiconductor Wafer Fabrication”. *IEEE Transactions on Semiconductor Manufacturing* 33(1):1-12.

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