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SIMULATION FOR AN ENERGY-EFFICIENT SEMICONDUCTOR MANUFACTURING NETWORK

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ABSTRACT

The semiconductor industry plays an important role in reducing carbon emissions and facilitating CO_2 savings through energy-saving applications, while also generating a significant CO_2 footprint during the manufacturing process of chips. Despite this, microchips in end-applications have the potential to save CO_2 several times greater than the emissions generated. Chip manufacturers are required to be transparent in reporting the CO_2 emissions and customers are demanding to reduce the footprint and to increase the handprint. In this paper, we present a simulation study which analyzes the energy consumption of two exemplary semiconductor products to assess the ratio of fixed and variable energy consumption. In addition, the paper analyzes the most energy consuming processes and the linkage between the capacity utilization and the energy consumption in a typical semiconductor facility. The paper suggests for future work to analyze the handprint as well and to investigate the relation between the footprint and handprint.

1 INTRODUCTION

The global semiconductor market value is expected to grow from 590 bn USD in 2021 to 1.065 tn USD by 2030 (McKinsey & Company 2022). Semiconductors enable the reduction of carbon dioxide (CO_2) emissions through electrification and energy efficiency improvements in different applications e.g. renewable energies and electric vehicles (McKinsey & Company 2022). The footprint of chip manufacturers is expected to significantly increase as manufacturing capacity expands to meet the growing demand for semiconductors. Enquired by customers and regulators, chip makers are required to account their emission in the assessment of the semiconductor industry's footprint. To achieve this, semiconductor manufacturers must be reporting on scope 1, 2 and 3 emissions according to the greenhouse gas (GHG) protocol (BCG 2023). Simultaneously, the semiconductor industry facilitates CO_2 savings, also known as the "handprint". Consequently, the use-phase of chips in end products is resulting in an ecologically positive carbon footprint e.g. with significantly more CO_2 savings generated than emissions (Liebi 2011).

In the context of the semiconductor industry, the concept of handprint takes on a unique significance. While the industry's footprint represents the CO_2 emissions and energy consumption, the handprint measures the potential of CO_2 savings enabled using semiconductors in applications (Husgafvel 2021). This additional perspective on handprint allows us to view the semiconductor industry not just as an emitter of CO_2, but also as a facilitator of CO_2 savings.

In this paper, although, the handprint is not delved further, but for future research, it is essential to investigate the balance between the semiconductor industry's carbon footprint and handprint.

The semiconductor industry is characterized by short product life cycles driven by fast technological advancements and the persisting influence of Moore's law (Moore 1965). The semiconductor industry faces a highly volatile market causing inefficiencies in the supply-demand planning systems and capacity utilizations, specifically in time of upheavals (Aytac and Wu 2013). Moreover, the complex and lengthy semiconductor manufacturing process results in production lead times of up to six months or longer (Mönch et al. 2011). Among the various stages of semiconductor manufacturing, the cleanroom consumes the largest share of energy due to the unique environmental conditions required for wafer fabrication (Hu et al.

2020). Fabrication ("Fab") cleanrooms operate continuously and are 1.000 times cleaner than surgery rooms and 50 times more energy consuming than commercial buildings (Kircher et al. 2010). To optimize the energy consumption, it is important to understand the link between the fab capacity utilization and the energy consumption. Due to organizational and financial reasons the latter is only available at a building level and not on an equipment or process level.

Utilizing simulation methods can help bridge the gap in understanding the energy distribution and identifying the most energy-intensive processes in a typical semiconductor fabrication facility, providing valuable insights for optimization and energy efficiency improvements.

To address this challenge, this paper employs a discrete-event simulation approach (DES) based on an adapted version of the framework of Banks et al. (2005). The simulation model used a combination of real and synthetic data of two products in a semiconductor fab to assess the critical energy consuming processes and to examine how varying fab capacity utilization levels impact the energy consumption. The data of the investigated semiconductor fab between infrastructure (e.g. cleanroom) and equipment energy consumption shows that the ratio is 66% to 34% respectively. Thus, the ratio of fixed (including the infrastructure and some equipment) versus variable energy consumption, which in the past used to be estimated through a rule-of-thumb to be 70% to 30%. The study also elaborates the relationship between the fab capacity utilization and its impact on energy consumption by reconstructing the Ecological Operating Curve (EOC) adapted from the classical operating curve which links utilization to the flow factor (Hopf et al. 2022). This paper is structured as follows: Section 2 provides an overview of existing approaches in academic literature followed by the methodology employed in section 3. Subsequently, the simulation model will be proposed in section 4. The results will be discussed in section 5 leading to the conclusion in section 6.

2 LITERATURE REVIEW

As Liebi (2011) defined a methodology for the calculation of CO_2 emissions in the semiconductor supply chain, the frontend processes (FE) were identified as the major energy-consuming processes. In the global manufacturing network, the frontend encompasses activities building up integrated circuits (ICs) on the wafer surface to create microchips. The wafers can undergo up to 900 non-linear process steps in different fab locations resulting in the lead time of up to six months or longer even though most fabs operate in a 365/24 mode (Mönch et al. 2013). To enable production in a particle-free environment, clean rooms must maintain a distinct level of temperature, air pressure, humidity, and cleanliness (Ma et al. 2021) to operate on a submicron or nano level (Ehm and Lachner 2016). Maintaining cleanroom conditions implies a hundred air changes per hour (Kircher et al. 2010). For the maintenance of the necessary humidity, chillers and heaters are installed and act as fixed energy consumers. The initial step that creates material layers on a clean wafer is oxidation, deposition, or diffusion process, imposing a temperature between 900-1200°C (Gopalakrishnan et al. 2010). Manufacturing equipment such as thermal evaporators, mask aligners and surface profilers can be seen as variable energy consumers. The backend (BE) of the semiconductor supply chain involves several critical steps, including dividing the wafer into individual microchips, connecting them to outside pins through die attach and wire bonding processes, and followed by testing for quality control (Ehm and Lachner 2016). Compared to the BE, the FE represents by far the most energy- and capital-intensive part of the semiconductor supply chain. Therefore, the focus of this paper lies in the FE.

The objective of this semiconductor supply chain simulation is to address the energy-efficiency topic based on the 4 levels of aggregations of supply chain outlined in Figure 1. Simulations allow to mathematically model and analyze the behavior of prevailing systems in a cost-efficient and time-independent manner distinguishing between discrete-event, agent-based and system dynamics simulations (Banks et al. 2005). Diverging assumptions can be tested by the adjustment of parameters providing transparency in the entity dependencies of systems (Borshev and Filippov 2004). Discrete-event simulations (DES) portray entities following a successive series of process blocks that symbolize real manufacturing activities (Borshev and Filippov 2004). On the contrary, agent-based simulations (ABM) are used to represent interacting instances on a higher abstraction level (Grigoryev 2022). Thirdly, system dynamics

(SD) imitate the interaction between numerous parties on a strategic level, for instance, of an end-to-end supply chain (Sterman 2000). Since manufacturing processes are portrayed, the DES is chosen in this study.

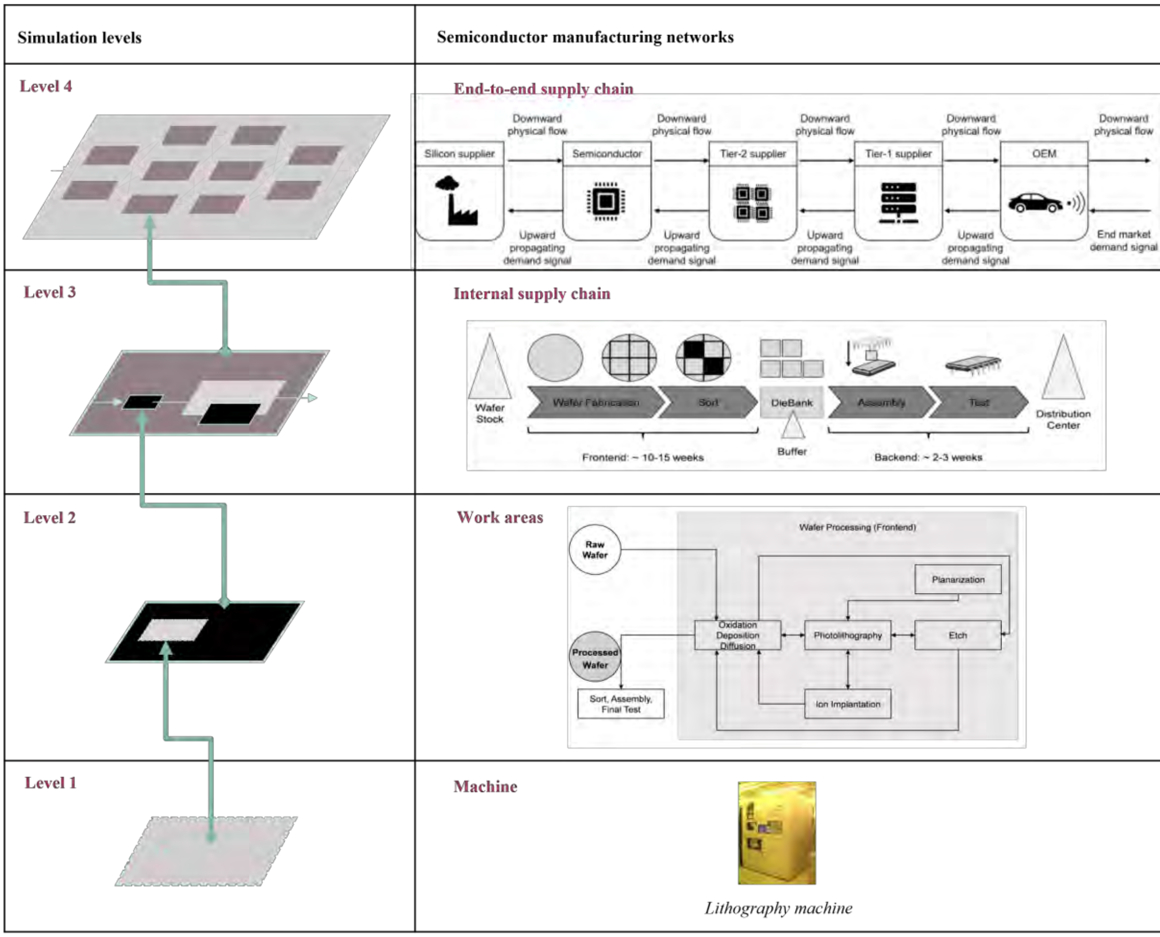

Figure 1: Simulation levels in semiconductor manufacturing adapted from Adan et al. (2012) and Fowler et al. (2015).

Yorck von Wartenburg (2013) investigates whether the global transportation networks for a flexible usage of idle capacities at different FE plants of a semiconductor manufacturer can lead to a better CO_2 balance implying a lower energy consumption per unit. For this reason, the emissions of the production facilities, transportation and scraped quantities are analyzed in a DES. It was found out that flexibility has a positive impact on the CO_2 balance in the FE process for products with an inconsistent demand. Hamed et al. (2018) delves deeper into the CO_2 emissions of the flexible capacity utilization and confirms the results by Yorck von Wartenburg (2013). Thiede (2012) focuses as well on the manufacturing systems on Level 3 in multiple case studies and formulates a methodology for the measurement of the fixed energy consumption.

Moreover, Resman et al. (2021) establishes a successive process guideline for the usage of simulations aiming to connect both the simulation model and the real system. The idea is to steer the real production system by the simulation model. Furthermore, Omar et al. (2015) present a hybrid simulation model that combines discrete and continuous modes by accurately synchronizing the sequence signal with the real-time frame. Consequently, the energy consumption of an automotive production facility can be anticipated considering manufacturing, stabilization of air conditions and equipment that uses energy.

Regarding the simulation level 2 of the work area, Guo et al. (2020) outline a flexible cellular manufacturing simulation that enables optimization of an air conditioner production line according to defined targets by the implementation of the parameter results. However, Seow and Rahimifard (2011) remark that the energy consumption shall be quantified on the process and more granular on the product level and therefore, the Embodied Product Energy (EPE) framework quantifies the required energy to create a manufacturing unit. In this regard, the simulation of a semiconductor fab by Hopf et al. (2022) evaluate the variable energy consumption of a generic product in a generic frontend process path. Consequently, a share of the energy consumption can be assigned to each process step in the frontend.

On the machine level e.g. level 1, Jeon and Prabhu (2013) model the energy consumption in a semiconductor fab and observe that the energy efficiency increases, if the equipment operates with lower power. Since machines can be configured flexibly and replaced corresponding to the product's requirements, the tool path can change accordingly. Thus, the energy consumption varies and can be reduced by predefined equipment adjustments and flexible machine sequencing (Jeon and Prabhu 2013). Since the Cycle Time (CT) can be defined as the average time a manufacturer needs to process a customer order, Hopp and Spearman (2011) noticed that the waiting i.e. queuing time increases exponentially to the capacity utilization of a workstation. Thus, the cycle time consists of the queuing as well the Raw Process Time (RPT) (Hopp and Spearman 2011). Fowler and Robinson (1995) capture the trade-off between the maximum usage of capacities and minimization of the cycle time with a rising queuing time in the concept of the Operating Curve (OC) see Figure 2. The idea is to find the optimum of the fab variability α (*alpha*) between the utilization of a workstation and the Flow Factor (FF) which represents the relation between the total CT and the RPT (Figure 2). Therefore, the FF reacts more sensitively at a higher capacity utilization as the queuing time rises (Fowler and Robinson 1995).

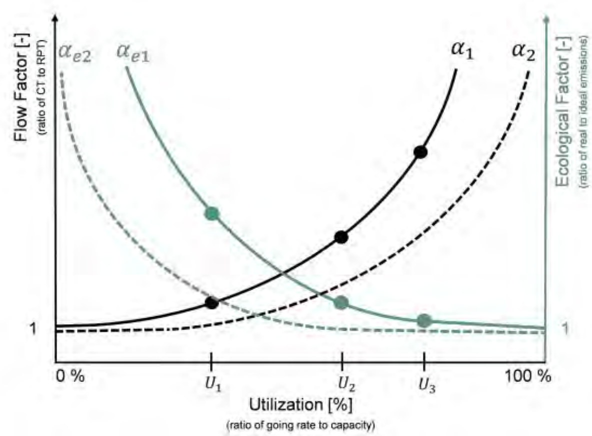

Figure 2: Schematic visualization of the economic and ecological operating curves by Hopf et al. (2022).

Hopf et al. (2022) extend the concept of the operating curve by an Ecological Factor (EF) to the Ecological Operating Curve (EOC) portraying the energy consumption of the FE manufacturing process in the semiconductor industry. If the machine capacities are fully exploited, the energy consumption per product would decrease and thus, the EOC declines as the EOC implies the relation between the available capacities and the actual throughout. Therefore, delving deeper into the energy consumption patterns of a semiconductor fab and identifying the most energy-intensive processes, as well as further exploring the EOC related to fixed energy consumption per product, is essential. The focus of this paper is to model the fixed and variable energy consumption in a semiconductor fab identified by Hopf et al. (2022) in detail using specific products with different tool paths instead of a generic product. Hence, the energy efficiency can be evaluated and consequently optimized.

The scope of the simulation in this paper is considering the fab level in a detailed granularity of machines. In a typical semiconductor manufacturing company, the concept of a global virtual factory is prevalent. This refers to the orchestration of the entire manufacturing network as if it were a single, unified entity. In the following section, we will explore the methodology and simulation approach.

3 METHODOLOGY

This section introduces the methodological approach for the conceptualization of the simulation model. A simulation model for the verification of the production conditions in a semiconductor fab of two products, namely Product A and Product B, is created. An entity-relationship diagram (ERD) according to Bagui and Earp (2011) highlights the process flow of the two products across the entire supply chain of a semiconductor manufacturer which were used in the simulation study.

3.1 Simulation approach

In this paper, the FE production environment of two products is simulated with a focus on two different product routes to grasp the process interdependencies. The DES model displays a sequence of FE operations in form of building blocks starting from a source and ending in a sink (The Anylogic Company 2019). The products pass as entities through the blocks enabling to track busy and idle states and thus, the energy consumption. Machines on Level 1 have been created based on the products' route of the two chosen products as described in the ERD diagram in Figure 3.

An ERD visualizes the entire database structure showing entities, their attributes, and their relationships. There are eight entities involved in this model, namely Supply Chain, Location, Facility, Route, Tool Groups, Product Type, Process Times, and Single Process Steps (SPS). Each entity is represented by a class and has its own attributes having a unique Primary Key (PK) and multiple Foreign Keys (FK). Some of these FKs are the PKs for other entities and help to link the different entities together. The ERD highlights the relationships between the entities and associated attributes in an overview. Each entity has an input and an output parameter. While the input parameters are input into the simulation model, the output parameters are calculated based on the different product routes of the product.

Each entity has a specific function and expresses how the product is manufactured and delivered across the supply-chain network. As shown in the ERD, a single product or wafer, has multiple points of contact in a supply chain. A Product Type, such as a diode or an integrated circuit, consists of one or many Routes which consists of different operations, which in turn broken down into single process steps (SPS). For every Route, Process Times data was obtained from the operations and controlling department for processes such as oxidation, lithography, ion implantation, etc. These process steps are performed in Tool Groups, which includes all the equipment and machinery necessary for performing the different operations to make different products. A Tool Group belongs to a Facility. A Facility is found in a Location, which is part of the Supply Chain. The network through which all these products go through is the Supply Chain which is globally spread across the world.

Real and qualified synthetic data collected from a typical semiconductor was used to model the data structure of the ERD. Energy consumption data is available on building granularity, for this study the energy consumptions for processes and equipment were obtained via a top-down analysis using parameters calibration similar to the approach from Hopf et al. (2022) and validated the results with measurements from selected tool groups and validation via expert knowledge. Even when fab is running in an idle state its energy consumption doesn't reach the value of zero, due to the warm steel state. The warm steel state means that the machines are ready to process wafers and set in stand-by mode implying that they still consume energy in this state. The cold steel mode on the contrary, means shutting down the machine but this would take up to a week to return to the environmental conditions before shutdown. Product A and Product B with 82 and 96 operating sequences respectively, each of which have corresponding SPS assigned to them depending on the type of operation sequence used. The chosen products represent a simplified version of chips where the data is available with the most energy important steps.

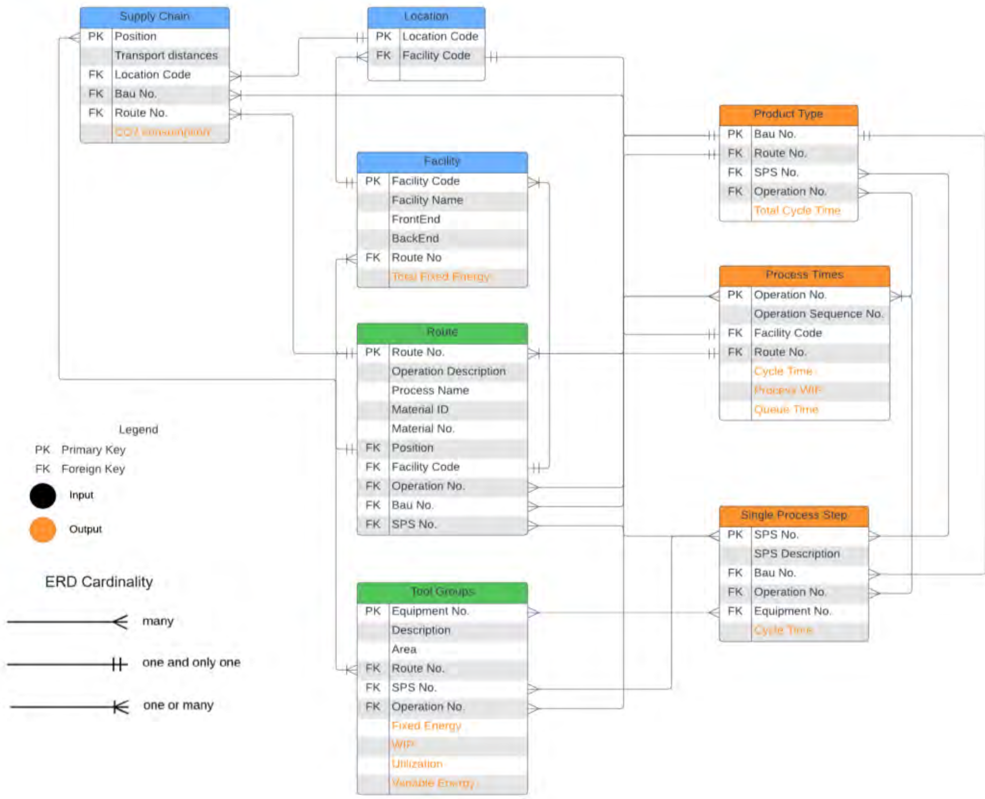

Figure 3: Entity-relationship diagram (ERD) representing the route and steps to produce semiconductor products from single equipment to supply chain level.

3.2 Simulation Setup

The simulation model was developed using the modelling software AnyLogic 8. The simulation model considers the re-entrant flow nature of the manufacturing process where operation sequences involve identical and repetitive processes. This results in wafer lots passing through the same machines multiple times before the completion of the production flow. Moreover, the same processes may require different SPS depending on the operation sequence of the current wafer lot. For instance, two oxidation steps may use different SPSs for two different operation sequences, depending on which oxidation step the wafer lot currently needs to undergo. The product route data contains the actual processing times and waiting times for each operation sequence of the wafer lot.

It is important to note that not all processes in semiconductor manufacturing are wafer or lot based. Some processes, such as oxidation, are processed in batches, where multiple wafer lots are combined and processed together in one machine. Typically, production processes involving furnaces are batched processes. The products' routes data identifies which processes are batched; the simulation model takes that into consideration. In actual production scenarios, batch sizes could vary with time and processes in regards of their availability and production demand. However, for this study, after a discussion with subject-matter experts from the fab, one batch size was chosen and used in the simulation. Figure 4 shows different processes that a wafer might undergo through in a fab.

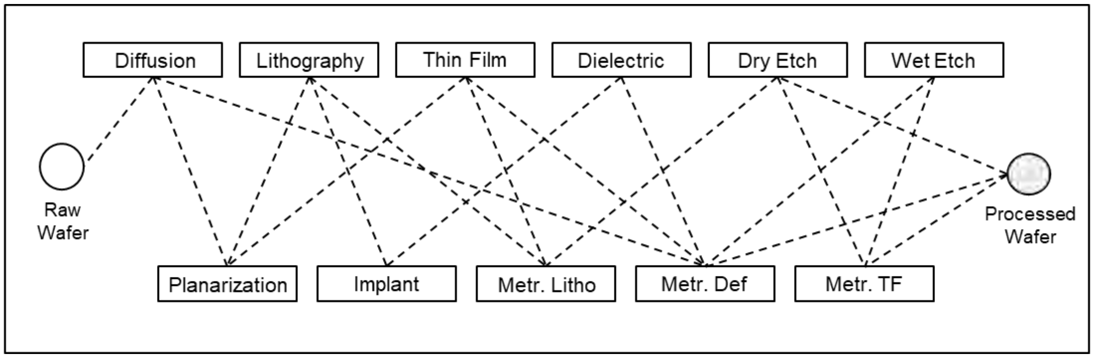

Figure 4: Schematic of different processes in a semiconductor fab.

The eleven-step framework outlined by Banks et al. (2005) provides a comprehensive methodology for developing a reliable and robust DES model. It begins with Problem Formulation, where the specific issue to be addressed is defined, followed by the Setting of Objectives and Project Planning to establish goals, and create a structured plan for development. The method then progresses to Model Conceptualization, Data collection, and Model Translation. According to Banks et al. (2005), Verification and Validation are then undertaken to confirm the model's accuracy and reliability, followed by Experimental Design for planned simulations. Finally, Simulation Runs and Analysis, Documentation and Reporting, as well as the Implementation of model insights, complete the structured approach. Following these guidelines, the first step for the Model Verification involves the analysis of the output after parameter adjustments. The process capacities are varied using default slider buttons in the AnyLogic simulation and the resulting trends in process machine utilizations.

The relationship between process capacity and machine utilization was found to be inversely proportional emphasizing longer waiting times and increased cycle times if the utilization increases. This trend was in line with expected results and verified the simulation results. The capacity values that ensured a smooth process flow were used for further simulation runs. The total Wafer Starts Per Week (WSPW) was another parameter that was varied to analyze the resulting trend which is an indication of the fab capacity. The WSPW for Product A was used as a parameter, and the WSPW for Product B was a variable dependent on WSPW for Product A. Increasing the WSPW for Product A automatically increased the WSPW for Product B, resulting in an increase in machine utilization levels for all the processes and an increase in cycle time. The maximum wafers that could be manufactured in the simulated fab were estimated using this gradual increase in WSPW. The presence of disruption between the input and output data was examined using several checkpoints in the process flow and regular console outputs at relevant points. A graphical representation of the model was used to verify the relationship trend between the total number of wafers manufactured and the total energy consumed per manufactured wafer.

A common assumption that an increase in the total number of wafers manufactured would reduce the energy consumed per manufactured wafer was verified and the results supported the assumption. The energy consumption for the process in the model, both fixed and variable, was verified through manual calculations using MS Excel and compared to the results generated from the simulation model. The outcome of both the real and the emulated process were found to be close – almost identical. Overall, the conceptualized simulation model is adequately verified and the next step in the simulation modeling process involves the validation of model assumptions. According to Banks et al. (2005) there are two types of assumptions in simulation modeling: structural and data driven. In this simulation model, a combination of both types of assumptions is considered. The energy consumption split as input in the simulation model assumes a fixed ratio between fixed and variable energy consumption and is deterministic. This could be improved by a study in future with stochastic shares of energy consumption to reflect the situation in reality.

Prior to this study the ratio between fixed and variable energy consumption was obtained through a rule of thumb approach by experts in the facilities and it was validated by Hopf et al. (2022) with an energy consumption study. The second assumption is data-driven where the relationship between variable energy consumption and utilization was initially assumed to be linear. This relationship was later explored by plotting various graphs to analyze the possibility of a non-linear relationship. The data validation is carried out by the comparison of the historically available total energy consumption data with the energy consumption data from the simulation study. The used data was scaled to the relevant maximum production capability of the simulated fab for validation purposes.

4 RESULTS

In this section, insights gained from the DES model are described. The experimental design used for simulation runs, and the outcome derived from these simulation runs along with results gained from various experiments using the simulation model outlined.

The simulation effects of the energy overview provide valuable insights into the distribution of total, fixed, and variable energy consumption. It is observed that a substantial portion of the total energy consumption is attributed to the fixed component encompassing infrastructure energy and the energy required for maintaining cleanroom conditions and the warm-steel state. The fixed consumption component accounts for approximately 90% in the model, leaving the remaining 10% as the variable energy component. These findings about the energy consumption are essential in understanding the dynamics of energy utilization within the simulated environment. Upon closer analysis of the energy consumption due to infrastructure and equipment, a shift in the ratio is discerned. The breakdown reveals that 66% of the energy is attributed to infrastructure (which is independent of the production quantity), while the remaining 34% pertains to equipment. This shift in the distribution of energy consumption provides critical insights into the relative contributions of infrastructure and equipment to the overall energy utilization within the simulated model. The correlation analysis of the actual dataset offers a comprehensive understanding of the relationship between the trend of simulated total energy consumption and the total number of wafers manufactured. Figure 5 shows energy consumption split at product *level.*

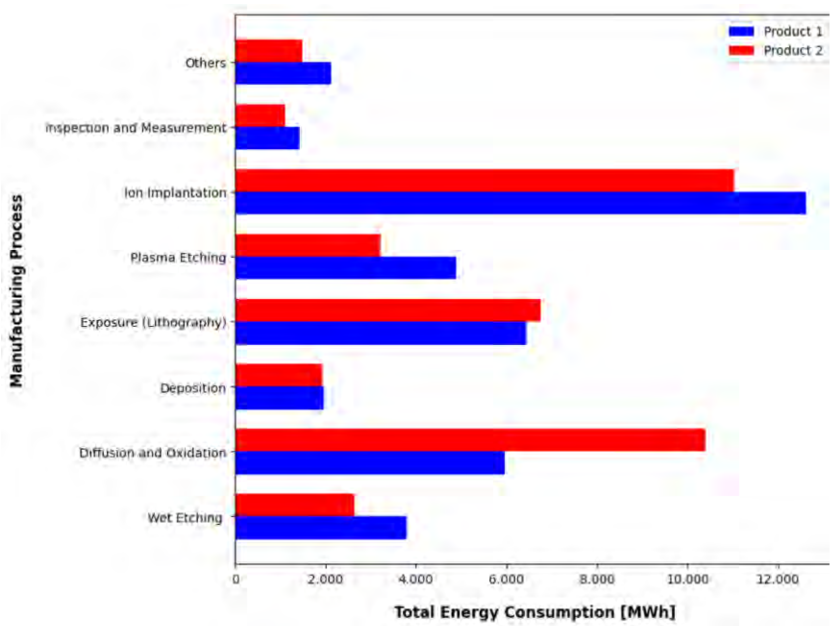

Figure 5: Energy consumption split at product level.

A slight positive trend in the total number of wafers manufactured juxtaposed with a slight negative trend in total energy consumption is observed. This observation aligns with the trends observed in the actual dataset suggesting similarities between the simulated and actual energy consumption patterns. The plausible explanation for this phenomenon is rooted in the improvement of efficiency over time in the fixed energy consumption of the fabrication facility. Despite the constant variable energy consumption in the simulation model, the direct inclusion of fixed energy consumption yields a discernible slightly negative trend. Moreover, the energy consumption shares for different processes are described shedding light on the process-wise energy split ratio. Significantly, ion implantation and oxidation processes emerge as the most energy-intensive, collectively accounting for nearly 55% of the total energy consumption of the fabrication facility.

This underscores the criticality of ensuring high utilization levels for these processes elucidating the pivotal role they play in the overall energy consumption landscape. The utilization levels of different processes over time offer valuable insights into the dynamics of process utilization within the simulated horizon. Ion implantation exhibits the highest utilization followed by exposure (lithography) and the oxidation process, mirroring the observed utilization levels in semiconductor production fabs. This alignment validates the simulated model in capturing real-world utilization patterns, thereby establishing the practical applicability of the insights derived from the simulation. The simulation model provides an understanding of the process-level split of total energy consumption. The delineation of energy consumption at the process level reveals that the ion implantation process commands the highest energy consumption, followed by oxidation, exposure (photolithography), plasma etching, wet etching, other processes, and inspection and measurement processes. This granular breakdown offers valuable insights into the energy consumption dynamics at the process level, elucidating the relative contributions of different processes to the overall energy utilization within the simulated environment.

The EOC concept as proposed by Hopf et al. (2022) is further investigated, with a specific focus on its application to multiple products using real data from a semiconductor production facility. The simulation model was enhanced by integrating the ecological factor (EF) equation, and the WSPW value was systematically augmented through parameter variation experiments to amplify model utilization. For every iteration, the α value of the fab was calculated using the formula given (1), where e $utiliz \neq 0$.

$$\alpha = (FF - 1) * \frac{1-utiliz}{utiliz} \tag{1}$$

Notably, α representing the fixed energy consumption share remained constant throughout the simulation runs aligning with the practiced rule of thumb and validated by Hopf et al. (2022). Incremental adjustments via the parameter variation experiments yielded diverse values for cycle time (CT) and utilization (*utiliz*), while raw process time (RPT) remained constant. Furthermore, the EF exhibited variability in response to fluctuating utilization levels attributable to changes in variable energy consumption. The resulting ecological factor (EF) and flow factor (FF) outcomes for varying utilization levels from the simulation experiment are depicted in Figure 6 providing a visual representation of the observed relationships.

The elbow of the operating curve (OC) remains a crucial indicator, denoting the peak utilization level within an acceptable range for the CT. In this context, the variable energy consumption rises proportionally with increased utilization levels. Consequently, it becomes evident that the variable energy consumption per manufactured wafer cannot be decreased as fab utilization levels rise. This leads to the conclusion that higher utilization levels result in a smaller EF, thereby reducing the energy consumption per manufactured wafer and enhancing the overall energy efficiency of the process. However, this need to be balanced with the flow factor since if utilization levels are high the FF is also high which results in slow production. An interesting area for future studies would be to analyze the impact of slow production on the energy footprint, this is due to the fact that the slow production could result in high ratio of scrap and consequently higher energy and ecological footprint which could be avoided by utilizing the OC and EOC concepts to stay within the region of producing at lower footprint and with lower cycle time to be able to meet customer demand efficiently. See Figure 6 for the results of the OC and EOC from the simulation model.

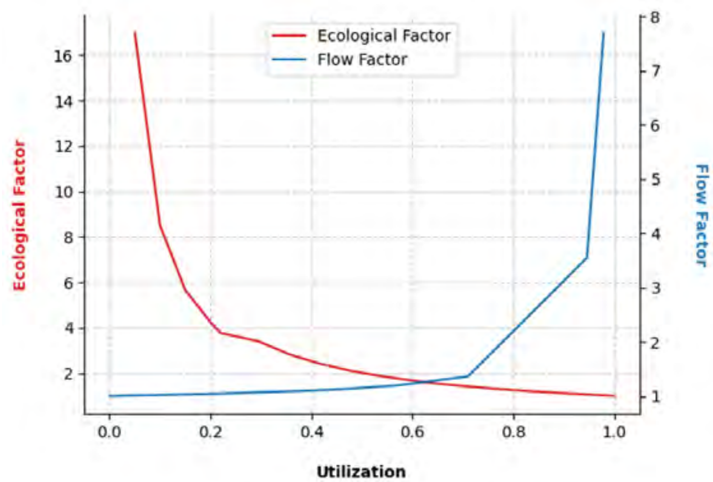

Figure 6: Simulations results showing the operating curve and the ecological operating curve.

The consideration of two products for designing the simulation model of the semiconductor manufacturing facility necessitates an exploration of the equipment energy consumption for each product and the split based on the process level. The ion implantation process emerges as the highest consumer of equipment energy for both products in alignment with the energy ratio split derived from the parameter calibration experiment. However, a noteworthy divergence is observed in the secondary consumption patterns wherein Product A exhibits the second-highest consumption in the exposure process, while Product B demonstrates the second-highest consumption in the oxidation process. This divergence is attributed to the distinct product routes for the considered products, underscoring the influence of product-specific process sequences on energy consumption patterns. The simulation model offers critical insights into the GHG emissions of the simulated fabrication facility. The simulated fab, operating solely on electrical energy (neglecting other emission forms because they are out of the scope of the study), yields to an average GHG emissions factor of 349 grams CO_2/KWh for electrical energy in Germany. This average energy consumption for the simulated fab translates to 1.72 KWh/cm^2, with a corresponding GHG emission of 0.6 kg CO_2 e/cm^2 aligning with current trends in the semiconductor industry. This understanding of the GHG emissions underscores the environmental implications of the simulated energy consumption patterns, thereby augmenting the applicability of the simulation insights in sustainability assessments.

In summary, the simulation results of the energy overview provide a comprehensive understanding of the distribution of total, fixed, and variable energy consumption within the fabricated environment (Table 1). The breakdown of energy consumption across different components and processes, coupled with insights into GHG emissions underscore the multifaceted utility of the simulation model in informing strategic decision-making and sustainability assessments within the semiconductor manufacturing domain.

Table 1: GHG emission overview of considered products based on exemplary data.

Product	Product A	Product B
Share of total wafers produced	59%	41%
Variable energy consumption per wafer [KWh]	32,5	45,7
GHG per manufactured wafer [kg CO_2 e]	11.3	15.9
GHG per cm^2 of manufactured wafer [grams CO_2 e / cm^2]	160	225

5 CONCLUSION

In conclusion, the developed simulation model effectively replicates the energy consumption patterns of a semiconductor fab within a global manufacturing network, enabling to derive the total energy consumption per product unit for further aggregation. The analysis of product routes for two distinct product types highlights the energy consumption differences, with a particular focus on the most energy-intensive processes, such as ion implantation and oxidation. The results suggest that structural changes in the FE operations are recommended to optimize manufacturing energy consumption.

The Ecological Operating Curve analysis implies that high-capacity utilization levels can reduce fixed energy consumption per product, albeit potentially increasing Flow Factor (FF) and waiting times. Future simulation runs should incorporate failure rates and adopt a probabilistic setting. Utilizing different datasets, such as those from other wafer fabs, can further validate the simulation model. Lastly, the GHG per cm^2 is derived from electrical energy.

Additionally, the study currently only evaluates the energy consumption or the footprint, and we recommend incorporating the handprint in future research for a comprehensive assessment of the holistic net CO2 balance. This should involve quantifying the CO2 savings resulting from semiconductors over their entire lifecycle and exploring strategies to maximize these savings through informed product offerings in the market. Future simulations could consider evolving towards a digital twin, continuously gathering real-time data from the fab energy systems, and replacing assumptions with actual data to enhance the model's accuracy and relevance.

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