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A PLANNING MODEL FOR INCORPORATING RENEWABLE ENERGY SOURCES INTO SEMICONDUCTOR SUPPLY CHAINS

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ABSTRACT

In this paper, we discuss a long-term planning approach for semiconductor supply chains. Since a single semiconductor wafer fabrication facility (wafer fab) needs a huge amount of energy to work as intended, the approach considers sustainability goals and production-oriented objectives. We are interested in determining how many wind turbines and solar photovoltaics need to be installed in a wafer fab to obtain a certain penetration of renewable energy while the prescribed demand is met. A mixed integer linear programming (MILP) model is established for a set of wafer fabs that work in parallel. Computational experiments are carried out to demonstrate the behavior of the model under certain experimental conditions.

1 INTRODUCTION

Semiconductor manufacturing deals with producing integrated circuits (ICs) on silicon wafers, thin discs made from silicon or gallium arsenide. Wafer fabrication, sort, assembly, and final test are the major stages required to manufacture ICs (cf. Mönch et al. 2013). The wafer fabrication part of the manufacturing process is carried out in wafer fabs. The ICs are built up layer-by-layer onto the wafers in wafer fabs. More than 40 layers exist for the most advanced products. After processing in the wafer fab, the wafers are sent to sort where electrical tests are carried out to identify defective dices. The probed wafers are then transferred to assembly facilities where dices of appropriate quality are put into a package. Finally, packaged dices are sent to test facilities where they are again tested to ensure that only products of high quality are delivered to customers. Wafer fab and sort are often called front-end, whereas assembly and test are called back-end. The semiconductor manufacturing process consists of up to 800 process steps, i.e. operations, and can take up to three months.

Wafer fabs belong to the most energy-intensive manufacturing systems due to the required cleanroom conditions and advanced machinery. As a result, the semiconductor industry consumes more energy than other industries, for instance, the steel or petrochemical industry (Yu et al. 2017, Mönch et al. 2018a). Long-term planning models deal with how demand can be met while profit is maximized simultaneously (Stray et al. 2006). The models compute release decisions for the different products per facility and period of the planning window. Moreover, it can be determined which facilities are opened or closed in the network during the planning window, typically several years.

Only a small body of literature is available that deals with sustainability issues in semiconductor supply chains (cf. Mönch et al. 2018a). This is especially true for integrating production planning decisions (Mönch et al. 2018b) with aspects of a sustainable and distributed generation (DG) system. We are only aware of Villarreal et al. (2013), Santana-Viera et al. (2015), and Ziarnetzky et al. (2017) where the number of wind

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turbines and solar photovoltaics is determined that need to be installed in a wafer fab to obtain a certain penetration of renewable energy and ensure a high profit. Simulation-based optimization is applied in these papers. However, the required strategic design decisions are typically made for an entire semiconductor network and not only for a single wafer fab. In the present paper, we propose a MILP model to compute how many wind turbines and solar photovoltaics need to be installed in the nodes of the semiconductor network which consists of a set of wafer fabs that operate in parallel. Computational experiments are carried out to demonstrate the behavior of the model under certain experimental conditions.

The paper is organized as follows. We describe the problem and discuss related work in the next section. The planning model is then proposed in Section 3. Next, the results of computational experiments with the planning model are presented in Section 4. Finally, conclusions and future work directions are discussed in Section 5.

2 PROBLEM DESCRIPTION AND ANALYSIS

2.1 Problem Statement

We consider a set F of wafer fabs that work in parallel. Such settings can be found in companies that work in the foundry mode (Mönch et al. 2018a). Our goal is to consider elements of a sustainable and DG system in strategic planning formulations for semiconductor supply chains. The generation system includes

- wind turbines (WTs)
- solar photovoltaics (PVs)
- substation with grid access
- net metering.

WTs and solar PVs have the highest priority in supplying the daily electricity of the wafer fabs belonging to F. Additional electricity can be hauled from the substation in the case of a power shortage. The surplus energy is returned to the main grid using a net metering system when the power delivered by the installed WTs and solar PVs exceeds the load. The electricity load resulting from manufacturing activities in the wafer fabs and the power provided by the DG system have to be modeled. Both the load and the power are uncertain since the wafer fabs, the wind power, and the solar radiation are stochastic quantities.

We are interested in determining which quantity of a certain product should be released in which period of the planning window to minimize the sum of backlogging, finished goods inventory (FGI) holding, and work in process (WIP) cost. Moreover, a cost term caused by using power provided by the substation is introduced. The amount of this energy is given as the difference of the overall load and the amount of power provided by renewable energy sources based on the number of WTs and solar PVs in a certain wafer fab. The following assumptions are made for the planning model:

- The total demand for the wafer fabs in F is deterministic.
- The energy consumption per lot of a certain product and per period in a given wafer fab is known.
- Using power provided by the substation in a certain period leads to additional cost.
- If the power provided by renewable energy sources is larger than the load in a given period, the surplus leads to a cost reduction.
- The power is a deterministic value in the planning model that is calculated based on the given number of WTs and solar PVs.

The expected profit is calculated based on the decisions made by a MILP formulation. We consider:

- revenue
- WIP cost

- backlogging cost
- FGI holding cost
- WT and solar PV equipment installation cost
- WT and solar PV operating and maintenance cost
- cost related to using power produced by the substation
- cost reduction by returning surplus energy to the main grid.

A certain amount of the overall load must be satisfied by renewable energy provided by WTs and solar PVs. A penalty term is used in the objective function if this constraint is not fulfilled. The load consists of a fixed load that results from running a wafer fab, for instance, to ensure clean room conditions, and a load that depends on the number of WIP lots of a certain product in a certain period.

It is important that the level of detail for modeling single wafer fabs in the MILP model is not too high since a set of wafer fabs is considered. Therefore, we will model only the capacity of bottleneck tool groups similar to MILP formulations for semiconductor master planning (cf. Ponsignon and Mönch 2012).

2.2 Discussion of Related Work

We discuss research related to network design decisions taking sustainability measures into account. A literature review for energy-efficient production planning and scheduling models is provided by Biel and Glock (2016). However, strategic planning models are not considered. The network design model studied by Wang et al. (2013) considers cost minimization and minimization of the environmental impact, mainly represented by transportation decisions, supplier selection, and installing environmentally-friendly equipment in newly built facilities. The set of Pareto-optimal plans is computed. However, WTs and solar PVs are not directly considered. A set of mid-term and operational planning models for supply chains is proposed by Benjaafar and Daskin (2013). It is shown how conventional cost and the carbon footprint can be both considered in the planning formulations. However, renewable energy resources are not taken into account in the proposed models.

Next, we discuss semiconductor-related work. Strategic planning models for semiconductor supply chains are proposed by Stray et al. (2006) and Rastogi et al. (2011). While typical process conditions of semiconductor supply chains are taken into account, sustainability issues are not modeled. Only a few papers propose semiconductor-specific planning models that incorporate sustainability aspects. A sustainable and DG system for a single wafer fab based on simulation optimization to determine an appropriate number of solar PVs and WTs for integrating renewable energy in addition to the main grid under uncertain wind speed and solar irradiance is proposed by Villarreal et al. (2013). A stochastic programming model to consider contract-based demand requests received by a wafer fab that owns onsite wind and solar generation units is established by Santana-Viera et al. (2015). A pay-in-advance scheme is modeled. Monte-Carlo simulation is applied to solve the stochastic programming model. However, the electricity load is an exogenous quantity in both models, i.e., the load is not directly linked to the production activities. The most pertinent work for the present paper is the integrated production planning formulation by Ziarnetzky et al. (2017) where this limitation is avoided, i.e., the load is determined based on production activities. However, only a single wafer fab is considered and the model is more operative by nature which contradicts to a certain extent the more strategic decisions of installing renewable energy sources. In the present paper, we extend the planning model of Ziarnetzky et al. (2017) to a set of wafer fabs operating in parallel in a strategic setting, i.e. monthly periods and a planning window of several years.

3 PLANNING FORMULATION

3.1 MILP Formulation

We assume that a finite planning window which consists of $t = 1, \dots, T$ equidistant planning periods is given. Moreover, a set of wafer fabs is available. We know which product processing steps are related to bottleneck (BN) work centers. We only model the capacity of BN work centers in detail to reduce the computational burden of the MILP formulation, similar to the master planning approach proposed by Ponsignon and Mönch (2012). The following sets and indices will be used in the model:

G: set of all products, $g = 1, \dots, |G|$
F: set of all wafer fabs, $f = 1, \dots, |F|$
$PV(f)$: set of all solar PV types that are available for wafer fab f, $m \in PV(f)$
$WT(f)$: set of all WT types that are available for wafer fab f, $n \in WT(f)$
$O(f,g)$: set of all BN process steps for product g in wafer fab f, $l \in O(f,g)$.

The following parameters will be used in the model:

$\omega_{gt}^{(f)}$: unit WIP cost for product g in period t in wafer fab f
$h_{gt}^{(f)}$: unit FGI holding cost for product g in period t in wafer fab f
$b_{gt}^{(f)}$: unit backlog cost for product g in period t in wafer fab f
D_{gt}: demand for product g in period t
$r_{gt}^{(f)}$: unit revenue for product g in period t for wafer fab f
$C_t^{(f)}$: capacity of the BN work center for wafer fab f in period t
$\alpha_{gl}^{(f)}$: processing time of the lth step of product g on the bottleneck work center for wafer fab f
$e_g^{(f)}$: energy consumption for one unit of product g for wafer fab f in a single period
$L_g^{(f)}$: lead time for product g in wafer fab f
$L_{gl}^{(f)}$: lead time for wafer fab f in number of periods from the release of the raw material of product g to the completion of BN operation l of product g
$APWT_{nt}^{(f)}$: average power provided by a single WT of type n in period t for wafer fab f
$APPV_{mt}^{(f)}$: average power provided by a single solar PV of type m in period t for wafer fab f
$ctWT_n^{(f)}$: construction time in periods for a single WT unit of type n for wafer fab f
$ctPV_m^{(f)}$: construction time in periods for a single PV unit of type m for wafer fab f
$ce_t^{(f)}$: cost for wafer fab f per unit of power taken from the substation in period t
$cr_t^{(f)}$: revenue for wafer fab f per unit of surplus power returned to the main grid in period t
$LF_t^{(f)}$: fixed load for wafer fab f, independent from producing chips for providing the cleanroom environment and for running machines in standby mode in period t
$\lambda^{(f)}$: minimum percentage of renewable energy penetration for wafer fab f
$\delta^{(f)}$: unit penalty cost for not reaching the target percentage of renewable energy penetration in wafer fab f
$iPV_m^{(f)}$: fixed installation cost for a single solar PV unit of type m for wafer fab f

$iWT_n^{(f)}$: fixed installation cost for a single WT unit of type n for wafer fab f

$ir^{(f)}$: interest rate for wafer fab f

$dpv^{(f)}$: number of periods for depreciation of a solar PV unit installed near wafer fab f

$dwt^{(f)}$: number of periods for depreciation of a WT unit installed near wafer fab f

$oPV_{mt}^{(f)}$: operating and maintenance cost for a single solar PV unit of type m installed near wafer fab f in period t

$oWT_{nt}^{(f)}$: operating and maintenance cost for a single WT unit of type n installed near wafer fab f in period t

$nwt_{max}^{(f)}$ maximum number of WTs that can be installed near wafer fab f

$npv_{max}^{(f)}$ maximum number of solar PVs that can be installed near wafer fab f.

The following decision variables will be used in the model:

$Y_{gt}^{(f)}$: output of product g in period t from the last operation of its routing in wafer fab f

$Y_{gtl}^{(f)}$: output of product g in period t from operation l of its routing in wafer fab f

$X_{gt}^{(f)}$: quantity of product g released into wafer fab f in period t

$W_{gt}^{(f)}$: WIP of product g at the end of period t in wafer fab f

$B_{gt}^{(f)}$: backlog of product g at the end of period t in wafer fab f

$I_{gt}^{(f)}$: FGI of product g at the end of period t in wafer fab f

$APS_t^{(f)}$: average amount of power provided by the substation for wafer fab f or surplus energy from wafer fab f sent back to the main grid in period t

$RE_t^{(f)}$: average amount of minimum renewable energy penetration shortage or additional renewable energy exceeding minimum renewable energy penetration in wafer fab f in period t

$ciPV_{mt}^{(f)}$: total depreciation cost of all operational solar PV units of type m near wafer fab f in period t

$ciWT_{nt}^{(f)}$: total depreciation cost of all operational WT units of type n near wafer fab f in period t

$nwt_{nt}^{(f)}$: number of operational WT units of type n near wafer fab f in period t

$npv_{mt}^{(f)}$: number of operational solar PV units of type m near wafer fab f in period t.

We use the abbreviations $x^+ \coloneqq \max(x,0)$ and $x^- \coloneqq \min(x,0)$ in the rest of the paper. Moreover, we will set $W_{g0}^{(f)} = I_{g0}^{(f)} = B_{g0}^{(f)} = 0, f \in F, g \in G$ if no specific initial value is specified. The model itself is given as follows:

$$\max \sum_{f\epsilon F}\sum_{t=1}^{T}\left\{\sum_{g\epsilon G}\left[r_{gt}^{(f)}Y_{gt}^{(f)}-\omega_{gt}^{(f)}W_{gt}^{(f)}-h_{gt}^{(f)}I_{gt}^{(f)}-b_{gt}^{(f)}B_{gt}^{(f)}\right]\right.$$
$$-\sum_{m\epsilon PV(f)}\left[ciPV_{mt}^{(f)}+oPV_{mt}^{(f)}npv_{mt}^{(f)}\right]-\sum_{n\epsilon WT(f)}\left[ciWT_{nt}^{(f)}+oWT_{nt}^{(f)}nwt_{nt}^{(f)}\right] \tag{1}$$
$$\left.-\left[ce_t^{(f)}APS_t^{(f)+}+cr_t^{(f)}APS_t^{(f)-}\right]-\delta^{(f)}RE_t^{(f)+}\right\}$$

subject to

$$W_{g,t-1}^{(f)}+X_{gt}^{(f)}-Y_{gt}^{(f)}=W_{gt}^{(f)}, f\epsilon F, g\epsilon G, t=1,\dots,T \tag{2}$$

$$\sum_{f\in F}\left[Y_{gt}^{(f)}+I_{g,t-1}^{(f)}-I_{gt}^{(f)}+B_{gt}^{(f)}-B_{g,t-1}^{(f)}\right]=D_{gt}, g\in G, t=1,\dots,T \tag{3}$$

$$\sum_{g\in G}\sum_{l\in O(f,g)}\alpha_{gl}^{(f)}Y_{gtl}^{(f)}\le C_t^{(f)}, f\in F, t=1,\dots,T \tag{4}$$

$$X_{g,t-\left\lfloor L_{gl}^{(f)}\right\rfloor}^{(f)}=Y_{gtl}^{(f)}, f\in F, g\in G, l\in O(f,g), t=\left\lfloor L_{gl}^{(f)}\right\rfloor+1,\dots,T \tag{5}$$

$$ciPV_{mt}^{(f)}=\begin{cases}\dfrac{1}{dpv^{(f)}+1}\left(1+ir^{(f)}\right)^{dpv^{(f)}}iPV_{fm}\left(npv_{mt}^{(f)}+1/2\left(npv_{m,t+ctPV_m^{(f)}}^{(f)}-npv_{mt}^{(f)}\right)\right), & f\epsilon F, g\epsilon G, t=1,\dots,T-ctPV_m^{(f)}\\ \dfrac{1}{dpv^{(f)}+1}\left(1+ir^{(f)}\right)^{dpv^{(f)}}iPV_{fm}npv_{mt}^{(f)} & f\epsilon F, g\epsilon G, t=T-ctPV_m^{(f)}+1,\dots,T\end{cases} \tag{6}$$

$$ciWT_{nt}^{(f)}=\begin{cases}\dfrac{1}{dwt^{(f)}+1}\left(1+ir^{(f)}\right)^{dwt^{(f)}}iWT_{fn}\left(nwt_{nt}^{(f)}+1/2\left(nwt_{n,t+ctWT_n^{(f)}}^{(f)}-nwt_{nt}^{(f)}\right)\right), & f\epsilon F, g\epsilon G, t=1,\dots,T-ctWT_n^{(f)}\\ \dfrac{1}{dwt^{(f)}+1}\left(1+ir^{(f)}\right)^{dwt^{(f)}}iWT_{fn}nwt_{nt}^{(f)}, & f\epsilon F, g\epsilon G, t=T-ctWT_n^{(f)}+1,\dots,T\end{cases} \tag{7}$$

$$LF_t^{(f)}+\sum_{g\in G}e_g^{(f)}W_{gt}^{(f)}-\sum_{n\in WT(f)}APWT_{nt}^{(f)}nwt_{nt}^{(f)}-\sum_{m\in PV(f)}APPV_{mt}^{(f)}npv_{mt}^{(f)}=APS_t^{(f)}, \quad f\in F, t=1,\dots,T \tag{8}$$

$$\lambda^{(f)}\left(LF_t^{(f)}+\sum_{g\in G}e_g^{(f)}W_{gt}^{(f)}\right)-\sum_{n\in WT(f)}APWT_{nt}^{(f)}nwt_{nt}^{(f)}-\sum_{m\in PV(f)}APPV_{mt}^{(f)}npv_{mt}^{(f)}=RE_t^{(f)}, f\in F, t=1,\dots,T \tag{9}$$

$$nwt_{nt}^{(f)}\ge nwt_{n,t-1}^{(f)}, f\in F, t=2,\dots,T, n\in WT(f) \tag{10}$$

$$\sum_{t=1}^{ctWT_n^{(f)}}nwt_{nt}^{(f)}=0,\ f\in F, n\in WT(f) \tag{11}$$

$$npv_{mt}^{(f)} \geq npv_{m,t-1}^{(f)}, f \in F, t = 2, \ldots, T, m \in PV(f) \quad (12)$$

$$\sum_{t=1}^{ctPV_m^{(f)}} npv_{mt}^{(f)} = 0,\ f \in F, m \in PV(f) \quad (13)$$

$$X_{gt}^{(f)}, Y_{gt}^{(f)}, Y_{gtl}^{(f)}, W_{gt}^{(f)}, B_{gt}^{(f)}, I_{gt}^{(f)}, ciWT_{nt}^{(f)}, ciPV_{mt}^{(f)},\ APS_t^{(f)},\ RE_t^{(f)} \geq 0, \quad (14)$$
$$f \in F, g \in G, t = 1, \ldots, T, l \in O(f,g), m \in PV(f), n \in WT(f)$$

$$nwt_{nt}^{(f)}, npv_{mt}^{(f)} \epsilon\ \mathbb{N}, nwt_{nt}^{(f)} \leq nwt_{max}^{(f)}, npv_{mt}^{(f)} \leq npv_{max}^{(f)}, \quad (15)$$
$$f \in F, g \in G, t = 1, \ldots, T, m \in PV(f), n \in WT(f).$$

The objective function (1) consists of three parts. The first part refers to the conventional profit, whereas the second and third part model the cost for solar PVs and WTs, respectively. WIP variables and WIP balance constraints (2) are included in the model to compute the WIP cost in the objective function for each wafer fab. The FGI material balance for all wafer fabs is given by constraint set (3). Constraint set (4) models that the total time required to process all operations at the BN work center in a given period t does not exceed the time available at that BN work center of wafer fab f, whereas constraint set (5) defines the relation between the time a lot of product g is released into wafer fab f and completing processing at BN operation l of product g. It is assumed that a lot becomes available to the next BN operation on its routing as soon as a lot is processed at a given operation. Moreover, we assume that an operation consumes capacity in the period that it is processed. The constraints (6) and (7) compute the depreciation cost for all solar PVs or WTs, respectively, which are operated at wafer fab f. Constraint set (8) sets the amount of energy taken from the substation or sent back to the main grid. The power shortage or surplus of the required minimum renewable energy penetration is ensured by the constraint set (9). The constraints (10) ensure that only new solar WTs can be installed in the periods of the planning window, whereas constraint set (11) models the installation time. The constraint sets (12) and (13) are used for the same purpose for the solar PVs. The nonnegativity of the decision variables is enforced by the constraint set (14). The constraint set (15) ensures the number of WTs and solar PVs are integers and bounded.

The MILP model (1)-(15) incorporates lead times $L_{gl}^{(f)}$ for the lth BN operation of product g in wafer fab f. Here, the cycle time (CT) is the delay between work being released and its emerging as output. Lead times are estimates of the CT used for planning purposes. The $L_{gl}^{(f)}$ values are computed recursively, taking into account the processing times of the operations between consecutive operations on the BN machines and flow factor values. Here, the flow factor of product g is defined as the ratio of the average time required for material started in the process to become available as FGI to the sum of the processing times of all its operations. Flow factor values are obtained from long simulation runs for a given BN utilization (BNU). In the MILP model, we apply integer lead times by rounding down the fractional estimates obtained from simulation. Therefore, the proposed MILP model is similar to the Simple Rounding Down (SRD) production planning formulation proposed by Kacar et al. (2013). The MILP model is initialized using half the mean demand over the planning window as initial FGI value.

3.2 Parameterization and Implementation Issues

We use a modified version of the MIMAC 1 simulation model (cf. Fowler and Robinson 1995) for a single wafer fab. The original model represents a large-scale wafer fab with 84 work centers and more than 200 machines. Typical semiconductor characteristics such as batch processing, i.e. several lots can be processed at the same time on the same machine, and sequence-dependent setup times are included in the model. Two products with reentrant process flows and instantaneous material transfer between successive operations are used by the model. Each product has a route with more than 200 process steps. The modified version is obtained by using routes obtained by concatenating the routes of the original model three times. We refer to this model as MIMAC 1 – 3X. The average CT is around 63 and 72 days for a BNU of 90% and between 44 and 61 days for a BNU of 70%. The stepper tool group forms the planned BN in each wafer fab. We use a period length of one month. We take the routes and the offered BN capacity from the simulation model.

Based on the MIMAC 1 – 3X simulation model, we generate normally distributed demand according to the planned BNU. Following Kacar et al. (2016), we generate stationary load (SL) demand that realizes a product mix of 1:1 for the two products. Moreover, we also consider time-varying (TV) demand. Here, we divide the planning window into three-period subintervals. For the scenarios with BNU=90%, the utilization for each subinterval is selected to be either 85% or 95% with a given probability p. The demand for each product is then set to achieve this BNU level. This leads to an average utilization level of 90% across all the periods.

A wind and solar power generator taken from Villarreal *et al*. (2013) is used. The wind power (P_W) and the solar PV power (P_S) are estimated and aggregated. The P_W values are generated according to:

$$P_W := \begin{cases} 0, & \text{if } 0 \le v_t \le v_c \\ \frac{1}{2}\eta_W \rho A_W v_t^3, & \text{if } v_c \le v_t < v_r \\ P_{\max,} & \text{if } v_r \le v_t < v_s \\ 0, & \text{if } v_s \le v_t \end{cases}, \tag{16}$$

where the wind speed v_t is distributed according to a Weibull distribution. The parameters of this distribution depend on the geographical location of the related wafer fab. The quantity ρ denotes the air density, A_W is the area covered by the turbine blades, $\eta_W = 0.5926$ denotes a conversion rate, and $P_{\max}$ is the maximum power capacity of the WT. The operating conditions in (16) are standby, constant, and cut-off power. These conditions are described by the WT's cut-in speed v_c, the rated speed v_r, and the cut-off speed v_s. The solar PV is modeled by the function

$$P_S(I_t, M) := M \eta_S A_S I_t \left(1 - 0.005\left(T_0 - 25\right)\right), \tag{17}$$

where the location-specific variable I_t. is the solar irradiance. The irradiance is the solar radiation received by a solar panel under clear sky conditions. Weather patterns such as a partly cloudy day or a cloudy day reduce the actual I_t value. The weather conditions typical for the wafer fab location are modeled using a discrete random variable M. The solar panel conversion rate, denoted as η_S, is set between 10-15%. Moreover, A_s denotes the panel area and T_o is the PV operating temperature.

Only a single WT and PV type is considered in the computational experiments. A maximum single WT and PV capacity of one MW is assumed. The average wind speed and its standard deviation are based on Chang et al. (2015) for a hub height of 100 m and are set to 8.0 m/s and 1.4 m/s, respectively. Cut-in, rated, and cut-off speed are 2.5 m/s, 11.0 m/s, and 54.0 m/s, respectively. The number of sunny days is 215, while the PV efficiency and skin temperature are 22.5% and 45 °C, respectively. The fixed load for providing the cleanroom environment, powering the recirculation air fans, and supplying ultrapure water and pure gases is 60% of the total wafer fab load (cf. Villareal et al. 2013). A total fixed load of 6173.798 MWh per month (Hu and Chuah 2003) is considered. The energy consumption for a single lot is derived from Hu and Chuah (2003). The average number of completed lots per year in the simulation model ensures a 40% power usage by manufacturing activities. The fixed installation cost for a WT and PV capacity of one MW is $2,025,000 and $2,493,000, respectively, while the annual operating and maintenance cost is $9,533.33 and $1,687.50 per month, respectively (National Renewable Energy Laboratory 2022). A payoff period of 12 years is assumed where the annual interest rate is 1%. Three levels of minimum percentage of renewable energy penetration, namely $\lambda^{(f)} \in \{0.20, 0.50, 0.70\}$, are investigated. The unit penalty cost for not reaching the target percentage $\delta^{(f)}$ is set to \$0.30 and \$0.72 per kWh. A revenue $cr_t^{(f)}$ per unit of surplus power returned to the main grid of \$0.06 per kWh is used (cf. OECD 2022), while the cost per unit of power taken from the substation $ce_t^{(f)}$ is \$0.15 per kWh (cf. National Public Radio 2022).

For the sake of simplicity, it is assumed that the wafer fabs in parallel are identical. The construction time in periods for a single WT or PV is one period. Moreover, we use $nwt_{max}^{(f)} = npv_{max}^{(f)} = 100|F|$ in the computational experiments. The cost settings are taken from Ziarnetzky et al. (2017) and Kacar et al. (2016). We use $\omega_{gt}^{(f)}$ =\$14,000, $h_{gt}^{(f)} = \$18{,}000$, and $b_{gt}^{(f)} = \$40{,}000$ per month. The unit revenue is set to $r_{gt}^{(f)} = \$80{,}000$, considering the CT values observed by the MIMAC 1- 3X simulation model.

The commercial solver IBM ILOG CPLEX 12.8 is used in the performed computational experiments. In order to be able to run multiple computations simultaneously, we utilize several services offered by Amazon Web Services (AWS). The computations are performed in the cloud using eight virtual CPUs (cores) of the types Intel Xeon Platinum 8175M and 8259CL, both operating at 2.5 GHz. 64 GB of RAM are assigned to most of the instances, while for some of the long-running instances a total of 107 GB of RAM is required.

4 COMPUTATIONAL EXPERIMENTS

4.1 Design of Experiments

We are interested in studying the behavior of the MILP model under different experimental conditions. We expect that the number of wafer fabs in parallel, the minimum amount of renewable energy penetration, and the penalty cost influences the behavior of the model. In a first set of experiments, we look at the computing times depending on the factor levels of the design. Moreover, we are interested in demonstrating that the number of installed WTs and solar PVs depends on the minimum percentage of renewable energy penetration and the value of the unit penalty cost for not reaching the target percentage of renewable energy penetration. In the last set of experiments, we are interested in demonstrating that the number of installed renewable energy resources follows the demand pattern, i.e., when the demand increases, more resources are installed. To avoid horizon effects towards the end of the planning window, we add 6 additional periods to each problem instance. Each of these additional periods has the mean demand over the last 3 regular planning periods as its demand.

Table 1: Design of experiments.

Factor	Level	Count
Number of wafer fabs $\|F\|$	1, 2, 10	3
Minimum percentage of renewable energy penetration $\lambda^{(f)}$	0.20, 0.50, 0.70	3
Unit penalty cost for not reaching the target percentage of renewable energy penetration $\delta^{(f)}$	0.00030, 0.00072	2
Length of the Planning Window T	12, 36, 60	3
Independent demand scenarios	SL (70%) SL (90%) TV (90%, $p = 0.75$) TV (90%, $p = 0.25$)	4
Independent demand replications		2
Independent replications of the wind and solar profile		2
Total number of problem instances		864

Overall, 864 problem instances are solved in the cloud environment.

4.2 Computational Results

We show the results of the first experiment in Table 2. Instead of comparing all problem instances individually, we group the results according to levels of factors. We report the relative MIP gap in %, the average computing time per instance, and the number of installed WT and solar PV units. We observe from Table 2 that the number of wafer fabs and the length of the planning window lead to large values of the MIP gap and to fairly high average computing times. The same is true for larger $\lambda^{(f)}$ values. A larger penalty term $\delta^{(f)}$ also causes under most experimental conditions a larger MIP gap and larger computing times. We can also clearly see from Table 2 that larger $\lambda^{(f)}$ and $\delta^{(f)}$ values lead to more installed WT and solar PV units as expected. Overall, the MILP is not practical for some instances when both the number of wafer fabs and the number of planning periods of the planning window are high. Although we only conjecture that the planning problem discussed in this paper is NP-hard, the computational experiments support this conjecture.

Table 2: Computational results for the different problem instances.

Factor/Level	MIP Gap (in %)	Computing Time (in min)	#WT	#PV
$\vert F\vert / T$				
1/12	0.00	0.00	0.00	78.22
1/36	0.00	0.01	2.42	78.46
1/60	1.22	8.79	4.52	78.42
2/12	0.00	6.87	0.00	156.05
2/36	19.20	43.02	3.80	156.51
2/60	58.37	83.59	9.26	156.82
10/12	70.31	120.02	0.00	784.54
10/36	265.52	120.11	10.90	764.03
10/60	117.54	119.93	39.94	723.28
λ / δ				
0.20 / 0.00030	14.70	47.04	0.14	143.85
0.50 / 0.00030	55.22	53.85	0.00	403.76
0.70 / 0.00030	61.13	60.25	0.00	433.33
0.20 / 0.00072	80.49	49.20	0.00	153.00
0.50 / 0.00072	106.73	57.76	0.02	416.95
0.70 / 0.00072	36.52	66.80	47.06	433.33

Moreover, we show in Figure 1 the ramp-up situation where low demand in the beginning leads to a later installation of renewable energy resources. Here, we aggregate over all instances with $T = 36$ and $\delta^{(f)} = 0.00072$. We observe from Figure 1 that the renewable energy base is installed after the first 12 periods when the demand is increased. Moreover, we can also see that the construction time for WTs and solar PVs is respected by the model.

5 CONCLUSIONS AND FUTURE RESEARCH

We proposed a long-term planning model that considers renewable energy, namely WTs and solar PVs, for a set of wafer fabs operated in parallel. The model tries to ensure a prescribed penetration level for using renewable energy. A MILP formulation was established for this problem. Designed computational experiments using the MILP model were carried out that demonstrated that the model shows several expected effects.

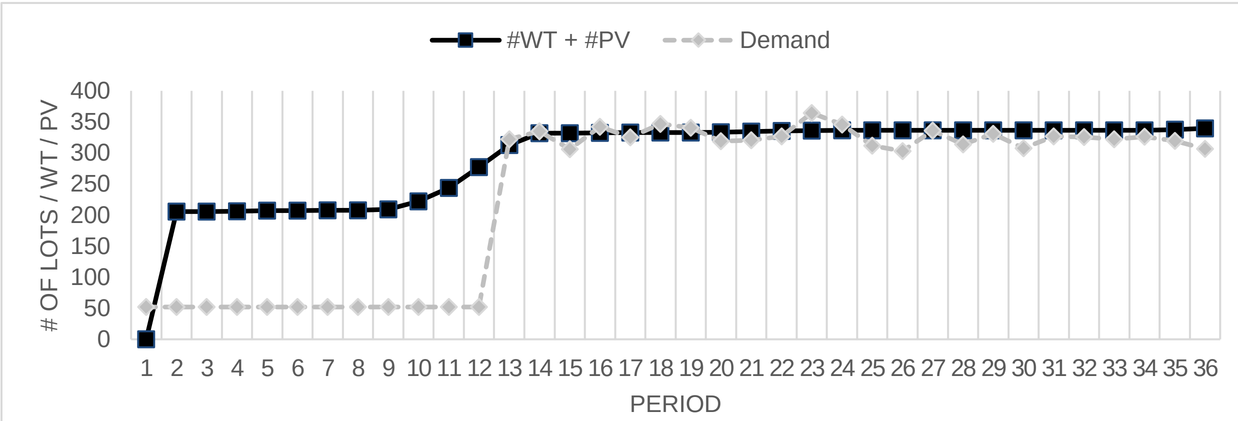

Figure 1: Situation for increasing demand over 36 periods.

There are several directions for future research. First of all, we are interested in a more detailed examination of the proposed MILP model. We strive to prove that the planning problem at hand is NP-hard. For instance, the impact of different WT and PV types and the resulting construction times should be studied. Moreover, it would be desirable to consider a set of heterogeneous wafer fabs and also location-, i.e. fab-specific wind and sun values. We are also interested in testing the proposed MILP model using modern large-scaled wafer fab simulation models as recently proposed by Kopp et al. (2020). As a third research avenue, we believe that simulation-based optimization in combination with discrete-event simulation can be used to make the release and installation decisions (Liu et al. 2011). Such an approach is desirable since it would allow taking into account the uncertainty of the manufacturing process and the weather uncertainty in a direct way.

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