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CRITICALITY MEASURES FOR TIME CONSTRAINT TUNNELS IN SEMICONDUCTOR MANUFACTURING

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ABSTRACT

Semiconductor manufacturing processes include more and more (queue) time constraints often spanning multiple operations, which impact both production efficiency and quality. After recalling the problem of time constraint management, this paper focuses on the notion of criticality defined in terms of time constraints at an operational decision level. Various criticality measures are presented. A discrete-event simulation-based approach is used to evaluate the criticality of machines for time constraints. Computational experiments conducted on industrial instances are discussed. The paper ends with some conclusions and perspectives.

1 Introduction

Semiconductor manufacturing processes are known to be the most complex manufacturing processes. They are characterized by long cycle times (8 to 12 weeks) with up to one thousand operations (often called *steps*), re-entrant flows, and heterogeneous complex machines. In addition to these challenging features, the constant development of new technology nodes fosters the multiplication of so-called *Time Constraints* (TCs) i.e., time limits to be respected between two operations in a given product route (Lima et al. 2021). More broadly, *Time Constraint Tunnels* (TCTs) are defined as a set of consecutive steps under at least one TC. Exceeding TCs may affect cycle times and production yield. Within a high-mix and highly time-varying manufacturing environment, operators working in a semiconductor manufacturing facility (*fab* in short) can have trouble detecting in real time the source (e.g., tense areas to focus) and the severity (e.g., duration of TCT overrun) of the risks of exceeding a TC when sending a lot in a TCT due to its complexity and variability. To tackle this problem, a simulation-based approach has been developed and Key Performance Indicators (KPIs) suggested to help the operators focus on different parts of the fab by Sadeghi et al. (2015), Lima et al. (2021) and Anthouard et al. (2022). Among these KPIs, the present paper proposes and discusses a number of criticality measures in terms of time constraints to support the management of TCTs at an operational decision level.

In the literature, TC management is a relatively recent topic. Problems including TCs in the constraints can be classified in three categories: Scheduling, capacity planning, and production control. To the best of our knowledge, no paper discusses the notion of criticality in terms of TCs. Criticality is mainly discussed for shifting bottleneck heuristics developed to solve scheduling problems minimizing the maximum lateness (*Lmax*) (Holtsclaw and Uzsoy 1996) or the Total Weighted Tardiness (TWT) (Zimmermann and Mönch 2006). In the shifting bottleneck heuristic, machine groups are ordered to be computed according to a criticality measure (Adams et al. 1988; Dauzère-Pérès and Lasserre 1993). The criticality measure chosen influences the sequence of the scheduling sub-problems to solve, and thus the quality of the best found solution. Different criticality measures can be found in the literature, focused mainly on the capacity of the fab and the tardiness. Holtsclaw and Uzsoy (1996) propose two criticality measures based on the workload of groups of machines and several approaches to compute *Lmax* as criticality measure. Pinedo (2012) uses a similar approach to study the TWT as a criticality measure. Zimmermann and Mönch (2006) propose a critical measure based on the previous measures and two other dynamic measures that rely on the workload of groups of machines and on a slack-based criticality measure comparing the processing time left and the due date of every lot. Aytug et al. (2003) propose static criticality measures based on the remaining processing time, the number of remaining operations, and the total machine load. Additionally, dynamic critical measures are proposed by studying the scheduling problem with an infinite capacity and looking at the violation (total, average, and maximal) of the capacity over time. For production control, Kopp et al. (2020) propose several dispatching schemes based on TC critical ratios and slack that could be adapted to create new measures.

To the best of our knowledge, criticality measures are not defined through the prism of TCs in the literature. The main difference between classical due dates and TCs is that a lot can be under multiple due dates at the same time when several TCs overlap in a single TCT, or have no due date if it is not under a TC. In addition, criticality measures are usually provided in the literature to support the search of the best machine sequence within the shifting bottleneck heuristics. This differs from our goal, which is to find the most critical machines in terms of TCs to identify the weak TC areas and avoid TCs being exceeded.

This paper presents criticality measures for time constraints. The context for our analysis does not take into account abnormal conditions (e.g., machine breakdowns or recoveries). Several measures from the existing literature are adapted in terms of TCs, and new measures are proposed. The conducted analysis shows that static measures are useful, but not sufficient to conclude on the criticality of machines. Strengthened by dynamic criticality measures, valuable support can be derived and a selection of machines proposed to the operators to focus on.

The remainder of this paper is organized as follows. Section 2 motivates and defines the problem under study. Criticality measures are detailed in Section 3. The proposed criticality measures are then evaluated and compared in Section 4 using full fab industrial instances. The interest of dynamic criticality measures is presented before concluding in Section 5.

2 TCT MANAGEMENT: PROBLEM STATEMENT AND SOLUTION APPROACH

As stated in Section 1, time constraints are hard to manage in a high-mix production environment. Because of the time-dependent character, operators need real-time indicators to know where they should concentrate their effort (lot, machine, TC). Moreover, sending a lot in a TCT is an important decision as once a lot is in the TCT, it must perform all its processing steps without being slowed down or stopped for too long to respect all the TCs. Thus, operators need to estimate the potential risks induced when sending lots in TCTs and identify the weak areas of the tunnels. This paper focuses on the definition and analysis of criticality measures in terms of TCs. The goal is to create a set of measures to characterize the criticality of the machines in a fab. Two components are required to characterize the criticality of a TC: A flag that indicates if the TC can be exceeded, and a time length measuring the time the TC has been exceeded.

Let us distinguish two evaluation modes of machine criticality in terms of TCs: **(i)** *Criticality under normal conditions:* Under normal conditions, the criticality of a given machine depends on the number of lots to be processed in TCs. If no action is taken, the machine will be overloaded by lots under the TCs and could lead to TCs being exceeded. Under normal conditions, all the machines in the fab stay in their original state. **(ii)** *Criticality under abnormal conditions:* Under abnormal conditions, the criticality of a given machine depends on its state. A downtime on the machine could lead to TCs being exceeded. Under abnormal conditions, states of machines can change (i.e., breakdown, disqualifications). By studying the criticality of the machines in a TCT, the risks of sending lots in the TCT can be reduced by focusing on the critical machines.

3 CRITICALITY MEASURES

In this section, a number of criticality measures are adapted to the problem of TCT management, and new criticality measures are also introduced. Measures are divided into two groups: **(i)** *Static measures:* Summary measures computed based on historical data related to the lot processing (see Section 3.1), **(ii)** *Dynamic measures:* Time-dependent measures computed dynamically using real-time data of the lots at their current steps (see Section 3.2). Table 1 details the notations used in the paper.

Table 1: Notations.

Notation	Description
R	Set of simulation runs r
H	Time horizon of the schedule
S_k	Set of steps s that can be processed on machine k
S_{cs}	Set of remaining steps $\tilde{s}$ of TC c after step s (included)
S^c_{kr}	Set of steps s under TC c processed on machine k during run r
S_{crst}	Set of remaining steps $\tilde{s}$ of TC c after step s (included) at period t on run r
S^c_{krt}	Set of steps s under TC queuing on machine k at period t of run r
C_s	Set of constraints c of step s
C_{rs}	Set of constraints c of step s entered during run r
C_{rst}	Set of constraints c of step s at period t of run r
K_s	Set of machines k qualified to process step s
d_{ks}	Delay between step s and its successor on machine k
p_{ks}	Processing time of step s on machine k
T^{CT}_s	Estimated cycle time for step s including the waiting time before and the processing time of s
τ_{crst}	Time a given lot performing step s passed under TC c during run r at period t
τ_{crs}	Time a given lot that performed step s passed under TC c at the end of run r
T^{max}_c	Maximum baseline duration of TC c
w_s	Weight associated to step s

3.1 Static Criticality Measures

Static criticality measures are usually fast to compute as they usually require no algorithm. A number of static criticality measures from the literature are adapted and presented in this section.

Static Total Tool Load (denoted by `STTL`**),** $m(\texttt{STTL}) \in \mathbb{R}^+$**:** Based on the processing times, this measure is introduced by Aytug et al. (2003) and Holtsclaw and Uzsoy (1996) to detect machines that could bottleneck the fab. Processing time is not the only factor causing bottleneck situations. With parallel multi-chamber machines, batch machines, and serial multi-chamber machines, processes can overlap. Measure `STTL` (i.e., time to process all the steps on a given machine) corresponds to the sum of d_{ks}, and the average of processing time p_{ks} of all the steps s in S_k processing on machine k:

$$m_k(\texttt{STTL}) = \sum_{s\in S_k} d_{ks} + \frac{1}{|S_k|} \times \sum_{s\in S_k} p_{ks} \tag{1}$$

To make measure `STTL` TC-aware (denoted by `STTL_TC`), we replace S_k by the set of processing steps under TCs in Equation (1).

Average Remaining Steps to Completion (denoted by `ARSC`**),** $m(\texttt{ARSC}) \in \mathbb{R}^+$**:** This measure is introduced by Aytug et al. (2003) and adapted for TCs. The intuition is that steps at the beginning of TCs are more critical as the lots have a lower priority. Lots could wait more in the first steps than in the last steps, and waiting in the first steps has more impact on the remainder of the routes than waiting in the last step. When TCs start to be critical (i.e., when the time left under TC is only of a few hours), the priority of the lots in the system increases automatically to speed up the lot in its last processing steps. In addition, `ARSC` takes into account that TCs overlapping more steps are more critical. Measure `ARSC` is computed as the average number of steps $|S_{cs}|$ to complete the TC of all steps processed on machine k as in Equation (2):

$$m_k(\texttt{ARSC}) = \frac{1}{\sum_{s\in S_k} |C_s|} \sum_{s\in S_k} \sum_{c\in C_s} |S_{cs}| \tag{2}$$

Average Remaining Processing Time (denoted by `ARPT`**), $m(\texttt{ARPT}) \in \mathbb{R}^+$:** This measure is presented by Aytug et al. (2003). The idea of `ARPT`, when extended to deal with TCs, is similar to `ARSC`, but instead of counting the steps left to complete the TC, the average processing time to complete every step until the completion of the TC is considered, as specified in Equation (3). Note that the average processing time is considered over all the machines that can perform the step.

$$m_k(\texttt{ARPT}) = \frac{1}{\sum_{s\in S_k}|C_s|}\sum_{s\in S_k}\sum_{c\in C_s}\sum_{\tilde{s}\in S_{cs}}\left(\frac{1}{|K_{\tilde{s}}|}\times\sum_{k\in K_{\tilde{s}}}p_{k\tilde{s}}\right) \tag{3}$$

Average Remaining Cycle Time (denoted by `ARCT`**), $m(\texttt{ARCT}) \in \mathbb{R}^+$:** The idea is the same as `ARPT`, but cycle time T^{CT} is used instead of the average processing time. T_s^{CT} considers both the waiting time at step s and its processing time, as follows in Equation (4).

$$m_k(\texttt{ARCT}) = \frac{1}{\sum_{s\in S_k}|C_s|}\sum_{s\in S_k}\sum_{c\in C_s}\sum_{\tilde{s}\in S_{cs}}T_{\tilde{s}}^{CT} \tag{4}$$

Total Weighted Tardiness (denoted by `TWT`**), $m(\texttt{TWT}) \in \mathbb{R}^+$:** This measure has been presented by Holtsclaw and Uzsoy (1996), Pinedo (2012) and Zimmermann and Mönch (2006). By extension to TCs, the interest of `TWT` is to support the detection of exceeded TCs during a given number of runs. Total weighted tardiness for machine k is computed as the average `TWT` on machine k on all simulation runs. `TWT` on a single simulation run on a machine is the sum of the exceeded time at the end of the run of all the TCs of the steps that could have been processed on machine k weighted by the number of machines that can process the step (see Equation (5)). An exceeded TC impacts all the machines that could have processed the steps in the TC.

$$m_k(\texttt{TWT}) = \frac{1}{|R|}\times\sum_{r\in R}\sum_{s\in S_{kr}^c}\left(\frac{1}{|K_s|}\times\sum_{c\in C_{rs}}\max\{0,\tau_{csr}-T_c^{max}\}\right) \tag{5}$$

3.2 Dynamic Criticality Measures

Dynamic measures are calculated by the simulation-based approach presented by Sadeghi et al. (2015), Lima et al. (2021) and Anthouard et al. (2022). These measures are tracked for each simulation run $r \in R$ at period $t \in H$, and descriptive summary statistics (e.g., average, min, max) are calculated on R.

Weighted Dynamic Tool Load Under TC (denoted by `WDTL`**), $m(\texttt{WDTL}) \in \mathbb{R}^+$:** Inspired from Zimmermann and Mönch (2006), this measure tracks throughout the simulation the time to process all steps queued under a TC in front of the machine. The computation of this measure is similar to `STTL_TC` (see Equation (6)). Note that it is weighted by the number of machines allowed to process step s as the queue is shared. A machine sharing its queue with other machines is less critical than a machine that does not share its queue, and a machine with a longer queue is more critical, as lots will tend to wait more before being processed and could thus exceed their TC.

$$m_{krt}(\texttt{WDTL}) = \sum_{s\in S_{krt}^c}\frac{d_{ks}}{|K_s|}+\frac{1}{|S_{krt}^c|}\times\sum_{s\in S_{krt}^c}\frac{p_{ks}}{|K_s|} \tag{6}$$

Weighted Slack (denoted by `WSLACK`**), $m(\texttt{WSLACK}) \in \mathbb{R}^+$:** This measure has been introduced by Zimmermann and Mönch (2006). `WSLACK` can be adapted for TCs, by assimilating the due date of a given lot to the minimum date to exceed any TC. The slack (i.e., the remaining waiting time allowed without exceeding the TC) of the lot waiting to process a step on a machine is computed, normalized by the number of processing steps to complete the TC, and weighted by the priority of the lot at the step (see Equation (7)).

$$m_{krt}(\texttt{WSLACK}) = \sum_{s\in S_{krt}} w_s\left(\max\left\{1,\min_{c\in C_{rst}}\left(\frac{T_c^{max}-\tau_{crst}-\sum_{\tilde{s}\in S_{crst}}\left(\frac{1}{|K_{\tilde{s}}|}\times\sum_{k\in K_{\tilde{s}}}p_{k\tilde{s}}\right)}{|S_{crst}|}\right)\right\}\right)^{-1} \tag{7}$$

Criticality Level (denoted by $\texttt{CL}$**),** $m(\texttt{CL}) \in \{0,1,2,3\}$**:** This measure provides a label comparing the time to process all the lots under a TC with the time left under the TC according to a threshold, denoted by β. The average time left under a TC for lots waiting in front of the machine at every simulation run is compared with the minimal, average, and maximal time seen in all simulation runs to process all the lots under the TC on the machine (see Equation (8)). The greater $m_{kt}(CL)$, the more complicated the processing of lots under a TC without exceeding the TC should be.

$$m_{kt}(\texttt{CL}) = \begin{cases} 3, & \text{if } \overline{\delta_{kt}} \leq \frac{1}{\beta} \times \min_{r\in R}\{m_{krt}(\texttt{WDTL})\} \\ 2, & \text{if } \frac{1}{\beta} \times \min_{r\in R}\{m_{krt}(\texttt{WDTL})\} < \overline{\delta_{kt}} \leq \frac{1}{\beta\times|R|} \times \sum_{r\in R} m_{krt}(\texttt{WDTL}) \\ 1, & \text{if } \frac{1}{\beta\times|R|} \times \sum_{r\in R} m_{krt}(\texttt{WDTL}) < \overline{\delta_{kt}} \leq \frac{1}{\beta} \times \max_{r\in R}\{m_{krt}(\texttt{WDTL})\} \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

$$\text{where } \overline{\delta_{kt}} = \frac{1}{|R|} \times \sum_{r\in R}\left(\frac{1}{|S^c_{krt}|} \times \sum_{s\in S^c_{krt}} \min_{c\in C_{rst}}\{\max(0, T_c^{\max} - \tau_{crst})\}\right)$$

Number of TCs Exceeded (denoted by $\texttt{NTCE}$**),** $m(\texttt{NTCE}) \in \mathbb{N}$**:** This measure counts the number of TCs exceeded in front of the machine at every period. Machines with more TCs exceeded are more critical.

Dynamic Weighted Tardiness (denoted by $\texttt{DWT}$**),** $m(\texttt{DWT}) \in \mathbb{R}^+$**:** This measure represents the dynamic version of $\texttt{TWT}$, and is linked to $\texttt{NTCE}$. At every period, the tardiness of the jobs in front of the machine is computed and weighted by the number of machines able to process the step (see Equation (9)). Unlike $\texttt{TWT}$, there is no repercussion on $\texttt{DWT}$ of previous machines when a TC is exceeded on the downstream machine. The idea is to observe when and on which machine a TC will be exceeded, and estimate the length of exceeded time.

$$m_{krt}(\texttt{DWT}) = \sum_{s\in S^c_{krt}} \sum_{c\in C_{rst}} \left(\frac{1}{|K_s|} \times \max\{0, \tau_{crst} - T_c^{max}\}\right) \tag{9}$$

Weighted Inverted Critical Ratio (denoted by $\texttt{WICR}$**),** $m(\texttt{WICR}) \in [0,\gamma]$**:** The critical ratio is commonly used in dispatching (Rose 2002). A ratio under 1 means the lot is behind schedule, and a ratio greater than 1 means the lot is ahead of schedule. In our case, the inverse of the critical ratio is computed and weighted with the number of machines able to process the step as a lot behind schedule is more critical than a lot ahead of schedule. To bound this measure, and in the case where a TC is exceeded, $\texttt{WICR}$ for the TC is bounded by a threshold, denoted by γ. Measure $\texttt{WICR}$ of machine k is then the sum of the highest $\texttt{WICR}$ for all TCs of all the jobs waiting on machine k at period t (see Equation (10)).

$$m_{krt}(\texttt{WICR}) = \sum_{s\in S^c_{krt}} \max_{c\in C_{rst}}\left\{\min\{\gamma, \texttt{WICR}_{ckrst}\}\right\}, \text{ where } \texttt{WICR}_{ckrst} = \begin{cases} \frac{\sum_{\tilde{s}\in S_{crst}} \left(\frac{1}{|K_{\tilde{s}}|} \times \sum_{k\in K_{\tilde{s}}} p_{\tilde{s}k}\right)}{|K_s|\times(T_c^{max} - \tau_{crst})}, & \text{if } T_c^{max} > \tau_{crst} \\ \gamma, & \text{otherwise} \end{cases} \tag{10}$$

Number of Lots Critical (denoted by $\texttt{NLC}$**),** $m(\texttt{NLC}) \in \mathbb{N}$**:** This measure counts the number of critical lots i.e., lots that could exceed or have already exceeded their TCs. A machine can be critical because critical lots are queuing in front of it. To estimate whether or not a lot is critical, measure $\texttt{WICR}$ is used and compared with a given threshold, denoted by α. At period t for machine k, the number of critical lots is computed as in Equation (11).

$$m_{krt}(\texttt{NLC}) = \sum_{s\in S^c_{krt}} LC_{krst}, \text{ where } LC_{krst} = \begin{cases} 1, & \text{if } \max_{c\in C_{rst}}\left\{\min\left\{\gamma, \texttt{WICR}_{ckrst}\right\}\right\} > \alpha \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

4 NUMERICAL EXPERIMENTS

The numerical experiments have been conducted on 45 industrial instances collected from a fab of STMicroelectronics, regularly extracted from June 2021 to April 2022. In these instances, 30% of the steps are under TC with T_c^{max} ranging from 1 hour (H) to 840H with a majority of short TCs (70% of T_c^{max} are below 24H and 40% of T_c^{max} range from 8H to 16H). TCTs include up to 25 TCs over 48 steps with an average of 3 TCs over 4 steps. TCs considered in these instances are both *end-to-start* (i.e., the TC starts at the end of a process and finishes at the beginning of another process) and *start-to-end* (i.e., the TC starts at the beginning of a process and finishes at the end of another process).

The machine criticality has been evaluated by using a discrete-event simulation-based approach, that relies on disjunctive graph modeling and list scheduling, which simulates N times the behavior of the full fab using a given dispatching rule. The output results in N different possible schedules allowing the extraction of statistical features. The simulation-based approach and instances are described by Sadeghi et al. (2015), Lima et al. (2021) and Anthouard et al. (2022). The following settings have been used: **(i)** The machine complexity and modus operandi (parallel multi-chamber, batch, serial multi-chamber) have been explicitly modeled. **(ii)** A dispatching rule using an exponential distribution based on the lot priority has been applied. **(iii)** The regular event triggering the extraction of dynamic data has been set to 1 hour and results in an average of 10 regular points extracted every 6 minutes. **(iv)** 100 runs have been performed for each instance, and a stopping condition limiting the simulation time up to 72 hours has been used, sufficient for real-time decisions. Thresholds α and β have been arbitrarily set to 0.8, and γ to 2. Cycle time T_s^{CT} is computed as follows: The waiting time is obtained by a statistical calculation based on the history of waiting times observed over the past weeks (see Chapter 4 of Dequeant (2017)). If no information is available, the waiting time is calculated according to Zachka's formula as defined by Mhiri et al. (2014). The processing times are based on the machine models provided by the Industrial Engineering experts.

4.1 Static Comparison between Criticality Measures

Let us apply the average Spearman correlation to study empirically the correlation between the proposed criticality measures (see Table 2). For all machines in the considered instances, the Spearman correlation has been calculated between every two measures and averaged over the set of instances. Table 2 shows no surprising correlation, except evident correlations such as the TOTAL values with the MAX values, and `DWT` with `NTCE` or `NLC`. Some medium correlations are less evident like `STTL_TC` with `WICR` and `WSLACK`, but otherwise, most of the other correlations were expected due to either the way of computing the measure or the correlation between the data used. A surprising result is `CL` that does not seem correlated to other measures, maybe due to its discrete nature.

To understand if the proposed measures identify the same subset of most critical machines among all the machines in the fab, a ranking of the machines has been made for each criticality measure. The resulting ranking lists have been compared, by highlighting the elements in common. It is worthwhile to note that the criticality of machines is one of the most vulnerable aspects in the fab, the exact ranking of these critical machines being less important. Let $\mathscr{S}_m^{\rho}$ be the set corresponding to the ρ% most critical machines according to measure m. The ranking provided by two measures m_1 and m_2 are compared in terms of similarity between sets $\mathscr{S}_1^{\bullet}$ and $\mathscr{S}_2^{\bullet}$. The Sørensen-Dice coefficient $DSC(\mathscr{S}_1^{\bullet}, \mathscr{S}_2^{\bullet}) \in [0,1]$ is applied to measure the similarity between two sets as follows:

$$DSC(\mathscr{S}_1^{\bullet}, \mathscr{S}_2^{\bullet}) = \frac{2 \times |S_1^{\bullet} \cap \mathscr{S}_2^{\bullet}|}{|\mathscr{S}_1^{\bullet}| + |\mathscr{S}_2^{\bullet}|}$$

The more $DSC(\mathscr{S}_1^{\bullet}, \mathscr{S}_2^{\bullet})$ is closer to 1, the more sets $\mathscr{S}_1^{\bullet}$ and $\mathscr{S}_2^{\bullet}$ are similar. Table 3 shows the average similarity between the sets of critical machines provided by the proposed criticality measures for $\rho = 15\%$ over the considered instances. The label `DATA_RETURNED` corresponds to the percentage of machines returned by the associated measure when asking the 15% most critical machines compared to the

Table 2: Spearman correlation (%).

	STTL	STTL_TC	ARSC	ARPT	ARCT	TWT	TOTAL_WDTL	MAX_WDTL	TOTAL_WSLACK	MAX_WSLACK	TOTAL_CL	MAX_CL	TOTAL_NTCE	MAX_NTCE	TOTAL_DWT	MAX_DWT	TOTAL_WICR	MAX_WICR	TOTAL_NLC	MAX_NLC
STTL	100	60	11	11	17	36	37	26	35	16	4	4	25	24	25	24	28	12	26	25
STTL_TC	60	100	45	55	51	70	84	76	70	55	25	24	45	45	44	44	64	52	49	48
ARSC	11	45	100	78	75	35	36	38	48	54	-7	-6	17	18	17	18	40	46	18	19
ARPT	11	55	78	100	70	39	54	56	51	52	0	1	20	20	20	20	48	48	24	25
ARCT	17	51	75	70	100	32	50	52	56	58	-2	-2	22	22	22	22	58	60	31	31
TWT	36	70	35	39	32	100	60	55	74	67	16	16	59	58	59	58	66	63	62	61
TOTAL_WDTL	37	84	36	54	50	60	100	95	68	54	42	41	47	46	46	45	74	64	55	54
MAX_WDTL	26	76	38	56	52	55	95	100	62	53	39	38	46	45	45	45	69	64	53	52
TOTAL_WSLACK	35	70	48	51	56	74	68	62	100	90	17	17	50	49	49	48	91	84	65	63
MAX_WSLACK	16	55	54	52	58	67	54	53	90	100	14	15	46	45	45	45	80	87	60	60
TOTAL_CL	4	25	-7	0	-2	16	42	39	17	14	100	99	23	23	23	22	19	19	25	25
MAX_CL	4	24	-6	1	-2	16	41	38	17	15	99	100	22	22	22	21	19	20	24	24
TOTAL_NTCE	25	45	17	20	22	59	47	46	50	46	23	22	100	100	100	99	48	53	82	83
MAX_NTCE	24	45	18	20	22	58	46	45	49	45	23	22	100	100	100	100	48	53	82	83
TOTAL_DWT	25	44	17	20	22	59	46	45	49	45	23	22	100	100	100	100	48	53	82	83
MAX_DWT	24	44	18	20	22	58	45	45	48	45	22	21	99	100	100	100	47	53	82	83
TOTAL_WICR	28	64	40	48	58	66	74	69	91	80	19	19	48	48	48	47	100	92	65	64
MAX_WICR	12	52	46	48	60	63	64	64	84	87	19	20	53	53	53	53	92	100	69	69
TOTAL_NLC	26	49	18	24	31	62	55	53	65	60	25	24	82	82	82	82	65	69	100	100
MAX_NLC	25	48	19	25	31	61	54	52	63	60	25	24	83	83	83	83	64	69	100	100

list of machines. More prominent than the Spearman correlation, the conducted analysis on the similarity between ranking lists further accentuates the disparities between static and dynamic measures. Table 3 also confirms other links between measures e.g.: **(i)** DWT and NTCE return similar lists at more than 90%, or **(ii)** WICR, NLC, and WSLACK return similar lists over 70%.

To sum up, excluding obvious correlations like the cycle time with the processing time or the remaining number of steps for completion of the TC, or the TOTAL with the MAX measures, other measures do not seem to be strongly correlated and lead to different results. Static measures give different results compared to dynamic measures and are not sufficient to state on the criticality of machines. Finally, some measures identify smaller sets of machines as critical as CL, NTCE, or DWT. More investigations need to be done to understand the scope of the information provided by each measure. In this sense, the link between dynamic measures and their interactions is investigated at a deeper level and illustrated in Section 4.2.

4.2 Dynamic Comparison between Criticality Measures

As stated in Section 2, the criticality under normal conditions is linked to the load and the management rules of the fab. As presented in Section 4.1, static and dynamic measures give different results when compared in a static way. In this section, dynamic measures have been studied in a dynamic way to better understand their behavior over time and surround the scope of the support they provide.

For the criticality under normal conditions, TWT, TOTAL_NTCE, and TOTAL_DWT highlight at the end of the simulation the risk of TCs to be exceeded. Studying them in a dynamic way adds extra information on when the TC is exceeded and can help to decide when to release a lot in a TCT, or to take other actions dedicated to preventing lots from exceeding their TCs. However, other measures are also relevant as the simulation does not take into account the multi-dimensional variability of the fab. NLC gives information

Table 3: Ranking similarity between criticality measures: 15% most critical machines (%).

	STTL	STTL_TC	ARSC	ARPT	ARCT	TWT	TOTAL_WDTL	MAX_WDTL	TOTAL_WSLACK	MAX_WSLACK	TOTAL_CL	MAX_CL	TOTAL_NTCE	MAX_NTCE	TOTAL_DWT	MAX_DWT	TOTAL_WICR	MAX_WICR	TOTAL_NLC	MAX_NLC	DATA_RETURNED
STTL	100	58	36	33	35	25	19	22	16	13	11	10	22	21	22	21	14	12	18	16	15
STTL_TC	58	100	36	43	39	36	35	36	20	11	25	23	34	32	32	32	20	16	27	25	15
ARSC	36	36	100	50	65	4	13	20	10	17	6	6	15	17	16	17	8	14	8	13	15
ARPT	33	43	50	100	58	7	32	38	19	17	19	19	19	19	18	18	22	19	19	20	15
ARCT	35	39	65	58	100	6	25	31	21	25	11	11	20	20	19	20	20	23	19	22	15
TWT	25	36	4	7	6	100	37	35	44	29	28	26	48	45	46	45	37	34	47	42	15
TOTAL_WDTL	19	35	13	32	25	37	100	77	43	25	48	43	52	49	51	49	54	45	60	56	15
MAX_WDTL	22	36	20	38	31	35	77	100	40	25	42	39	54	53	53	52	50	45	58	56	15
TOTAL_WSLACK	16	20	10	19	21	44	43	40	100	69	37	35	47	44	43	42	73	65	67	61	15
MAX_WSLACK	13	11	17	17	25	29	25	25	69	100	27	28	36	35	33	33	53	60	50	50	15
TOTAL_CL	11	25	6	19	11	28	48	42	37	27	100	90	37	36	37	36	39	39	43	42	17
MAX_CL	10	23	6	19	11	26	43	39	35	28	90	100	35	35	35	34	36	37	39	40	18
TOTAL_NTCE	22	34	15	19	20	48	52	54	47	36	37	35	100	90	89	86	49	55	66	69	17
MAX_NTCE	21	32	17	19	20	45	49	53	44	35	36	35	90	100	91	91	47	56	63	69	17
TOTAL_DWT	22	32	16	18	19	46	51	53	43	33	37	35	89	91	100	94	48	56	63	68	17
MAX_DWT	21	32	17	18	20	45	49	52	42	33	36	34	86	91	94	100	47	56	61	67	17
TOTAL_WICR	14	20	8	22	20	37	54	50	73	53	39	36	49	47	48	47	100	75	77	69	15
MAX_WICR	12	16	14	19	23	34	45	45	65	60	39	37	55	56	56	56	75	100	73	76	15
TOTAL_NLC	18	27	8	19	19	47	60	58	67	50	43	39	66	63	63	61	77	73	100	84	15
MAX_NLC	16	25	13	20	22	42	56	56	61	50	42	40	69	69	68	67	69	76	84	100	15
DATA_RETURNED	15	15	15	15	15	15	15	15	15	15	17	18	17	17	17	17	15	15	15	15	0

of lots close to exceeding their TCs and constituting an actual risk. Measures such as `WDTL`, `CL`, `NLC`, or `WSLACK` need to be studied dynamically to understand how machines are overloaded by lots under TCs. When these measures present large values, it is a sign that it can be complicated to process lots under a TCT without exceeding their TCs. A simulation time horizon up to 72 hours could be insufficient for these measures to inform on TC violations. Sending a lot at specific time t in a TCT with large `WDTL`, `CL`, `NLC`, or `WSLACK` could lead to TCs being exceeded after the end of the simulation depending on when the peak of these measures is reached. A major point worth noting is that simulating a longer time horizon implies larger computational times, which can be critical for real-time decisions.

Dynamic measures have been studied in a dynamic way to evaluate their predictive capabilities related to the TC violation, in particular: **(i)** If whenever TCs started to be exceeded (first triggers of `NTCE` without breaks), is the violation detected by measures not later than 48 hours before (see Table 4)?, or **(ii)** When criticality measures are triggered, does this indicate that TCs will be exceeded later by the end of 48 hours (see Table 5)?. The dynamic measures have been studied **(i)** independently to understand the behaviors of the measures with respect to `NTCE`, and (ii) combined to investigate the value of their interactions. To avoid any risk of exceeding TCs, the trigger values of `DWT`, `NTCE` and `CL` have been defined to be strictly positive. Note that measure `CL` is critical when positive, by definition. For this reason, only `NTCE` is represented as `DWT`, and `NTCE` gives similar information. The trigger values for `WDTL`, `WICR`, `NLC` and `WSLACK` have been arbitrary defined equal to their average values for the instance and machine under study. The idea is to detect peaks in the signal sent by measures, that could be a sign of a machine being critical. Tables 4 and 5 represent the average values for all the machines of all the instances. The row `Trigg` indicates the average percentage of times, per machine and instance, that measures are triggered.

Table 4: Percentage of criticality measures detecting an NTCE event before it happens (%).

	t-46H,t-48H	t-43H,t-45H	t-40H,t-42H	t-37H,t-39H	t-34H,t-36H	t-31H,t-33H	t-28H,t-30H	t-25H,t-27H	t-22H,t-24H	t-19H,t-21H	t-16H,t-18H	t-13H,t-15H	t-10H,t-12H	t-7H,t-9H	t-4H,t-6H	t-1H,t-3H	t	Trigg
NTCE	33	35	36	38	39	41	42	43	44	44	45	46	48	48	49	40	100	39
MIN_WDTL	53	50	48	48	46	46	44	44	44	43	44	43	43	44	44	43	39	29
AVG_WDTL	63	62	60	58	57	56	55	54	53	53	53	53	53	53	54	53	50	39
MAX_WDTL	62	62	62	62	62	63	64	63	63	64	64	64	64	64	64	64	53	43
CL	3	3	3	3	3	4	4	3	4	3	3	4	5	6	8	10	10	18
WICR	54	53	51	52	52	53	52	52	52	52	52	52	52	53	54	52	57	39
NLC	39	38	37	38	39	40	41	41	42	42	42	43	44	45	46	49	58	29
WSLACK	61	58	58	59	58	57	55	55	55	54	55	54	54	54	55	55	51	41
MIN_WDTL & AVG_WDTL	43	41	39	37	36	36	35	34	33	33	34	34	34	35	36	35	34	26
MIN_WDTL & MAX_WDTL	37	35	34	34	32	33	32	32	31	32	32	33	33	34	34	34	30	24
MIN_WDTL & CL	2	2	2	2	2	2	2	1	1	1	1	1	2	3	4	5	5	9
MIN_WDTL & WICR	29	25	24	24	23	23	23	22	22	22	22	21	21	22	23	23	25	17
MIN_WDTL & NLC	23	21	21	21	20	20	19	20	20	19	18	18	18	19	19	22	28	15
MIN_WDTL & WSLACK	32	27	26	27	25	25	23	24	23	23	23	22	22	23	24	24	24	18
AVG_WDTL & MAX_WDTL	50	51	49	48	47	47	46	46	45	46	46	46	46	47	47	47	42	34
AVG_WDTL & CL	2	2	2	2	2	2	2	2	2	2	2	2	3	3	5	6	6	11
AVG_WDTL & WICR	33	32	30	30	30	29	29	29	28	27	28	27	27	29	30	29	32	22
AVG_WDTL & NLC	26	25	24	24	23	23	23	24	23	23	23	22	23	24	25	28	35	19
AVG_WDTL & WSLACK	35	34	32	32	31	30	29	28	28	27	28	27	27	28	30	30	29	22
MAX_WDTL & CL	2	2	2	2	2	2	2	2	3	2	2	3	3	4	5	6	6	12
MAX_WDTL & WICR	32	31	30	31	31	31	32	32	32	32	32	32	32	34	35	33	33	25
MAX_WDTL & NLC	25	24	24	25	25	26	26	27	27	27	27	27	28	30	30	32	36	20
MAX_WDTL & WSLACK	34	32	32	32	32	32	32	32	32	32	32	32	32	33	34	34	30	24
CL & WICR	2	2	2	2	2	2	2	2	2	2	2	2	2	3	3	4	4	11
CL & NLC	2	2	2	2	2	2	2	2	2	2	2	2	2	2	3	4	5	10
CL & WSLACK	2	2	2	2	2	2	2	2	2	2	2	2	2	3	4	5	5	11
WICR & NLC	31	31	30	31	31	32	33	33	34	34	34	35	36	37	38	40	48	25
WICR & WSLACK	45	42	41	42	42	41	40	40	39	40	40	40	40	40	42	41	42	31
NLC & WSLACK	29	28	27	28	27	27	27	28	28	28	28	28	30	30	31	33	39	22
VALID_DATA	27	30	34	37	40	43	47	50	53	58	62	67	72	78	84	88	100	0

The Trigg values in Table 4 and 5 can be different, as Table 4 explores the data from the machines triggered by NTCE, whereas in Table 5 every column examines the data of the machines triggered by the criticality measure in the respective column. In other words, in Table 5, the Trigg value represents the average percentage of times, per machine and instance, whose measures are triggered by a machine. The column VALID_DATA in Table 4 represents the percentage of data retrieved for every NTCE event. As the simulation runs for 72 hours, it was only possible to obtain a full 48 hours of historical data from the simulation 27% of the time, which means that an NTCE event occurred within the first 48 hours of the simulation 73% of the time.

Consider Tables 4 and 5. The first finding extracted from Table 5 is that whenever an NTCE event is triggered, it tends to stay triggered for the next 48 hours in 58% of the cases. Second, even if CL is weak, compared to the other measures when detecting NTCE events in Table 4, its triggering is more likely to predict a violation of the TC in the future more clearly than other measures. The CL detection seems to increase to 37% between 6 to 15 hours after the measure has been triggered while the NTCE detection

Table 5: Percentage of criticality measures predicting a NTCE event after being triggered (%).

	t	t+1H,t+3H	t+4H,t+6H	t+7H,t+9H	t+10H,t+12H	t+13H,t+15H	t+16H,t+18H	t+19H,t+21H	t+22H,t+24H	t+25H,t+27H	t+28H,t+30H	t+31H,t+33H	t+34H,t+36H	t+37H,t+39H	t+40H,t+42H	t+43H,t+45H	t+46H,t+48H	Trigg
NTCE	100	96	90	86	83	80	77	75	73	71	69	68	66	64	62	60	58	39
MIN_WDTL	29	33	33	33	33	32	30	29	27	26	24	23	21	20	19	18	18	20
AVG_WDTL	18	20	20	20	20	19	19	18	17	16	15	14	14	13	13	12	12	34
MAX_WDTL	17	18	19	18	18	18	17	16	16	15	14	13	13	12	11	11	11	41
CL	35	36	37	37	37	37	36	36	35	35	34	33	33	32	31	31	30	51
WICR	19	20	20	19	18	17	16	15	14	13	12	12	11	10	10	9	9	41
NLC	62	64	62	59	56	53	50	47	44	41	39	36	34	32	30	28	27	28
WSLACK	20	22	22	22	21	20	19	18	17	17	16	15	14	14	13	12	12	36
MIN_WDTL & AVG_WDTL	32	35	35	35	34	33	32	30	28	26	24	22	21	19	18	17	17	17
MIN_WDTL & MAX_WDTL	34	37	38	37	36	35	33	31	29	27	24	22	21	19	18	17	16	16
MIN_WDTL & CL	55	56	57	57	56	55	53	51	49	47	44	42	39	37	35	33	31	23
MIN_WDTL & WICR	39	41	41	40	37	35	32	30	27	24	21	19	17	15	14	13	12	11
MIN_WDTL & NLC	72	75	73	70	67	63	59	55	52	48	44	41	38	35	33	31	30	14
MIN_WDTL & WSLACK	41	44	44	44	42	39	37	34	31	28	26	24	21	20	18	17	16	11
AVG_WDTL & MAX_WDTL	20	22	22	22	21	21	20	19	18	17	16	15	14	13	12	12	11	28
AVG_WDTL & CL	41	42	43	42	42	40	39	37	35	33	31	29	27	25	23	22	21	28
AVG_WDTL & WICR	23	24	23	22	21	20	18	17	15	14	12	11	10	9	8	8	7	21
AVG_WDTL & NLC	64	67	65	62	58	55	51	48	45	41	38	35	32	30	28	26	25	18
AVG_WDTL & WSLACK	26	27	27	27	25	24	22	21	19	17	16	15	13	12	11	11	10	18
MAX_WDTL & CL	37	38	39	38	37	36	35	34	32	31	29	27	25	23	21	20	19	33
MAX_WDTL & WICR	20	21	21	20	19	18	16	15	14	12	11	10	9	8	7	7	6	26
MAX_WDTL & NLC	64	67	64	61	58	54	51	47	44	41	37	34	31	29	27	25	24	20
MAX_WDTL & WSLACK	23	24	24	23	22	21	20	18	17	16	14	13	12	11	10	9	9	22
CL & WICR	70	71	71	70	69	67	65	63	60	57	54	51	48	45	42	40	38	21
CL & NLC	83	84	84	83	82	80	77	75	72	68	65	61	58	54	51	49	47	28
CL & WSLACK	74	75	76	75	73	72	70	67	65	62	59	56	54	51	48	45	42	21
WICR & NLC	64	66	63	60	57	53	50	46	43	40	37	34	31	29	27	25	24	24
WICR & WSLACK	22	24	23	22	21	20	18	17	16	15	14	13	12	11	10	10	9	29
NLC & WSLACK	65	68	65	62	59	55	52	48	45	42	39	36	33	30	28	27	25	21

decreases in the same period range. This is consistent with the definition of this measure, which aims to detect when a machine is overloaded by lots under TC that will exceed their TC later. NLC is efficient **(i)** in detecting NTCE events when they occur then **(ii)** in predicting if there will be TCs exceeded, once triggered. As for measure CL, NLC seems to be able to predict TCs being exceeded in the 1 to 6 hours following an NTCE trigger. This is accurate with its definition of detecting lots in advance that have not exceeded their TCs, but are likely to exceed them in the near future. Other criticality measures present many false positive alarms. Table 4 shows rather promising results in detecting NTCE triggers, but when looking at Table 5, it appears that these measures are often triggered without TCs being exceeded. In addition, as the Trigg value is the same in Tables 4 and 5 for these measures, whether a TC is exceeded or the measure triggered, they seem to be triggered for the same length of time and do not add additional information about a TC being exceeded.

As expected, when measures are considered together and both triggered at the same time (see Table 5), the quality of prediction of having TC being exceeded is increased. The best results are provided by couple (CL, NLC), which predicts with an accuracy over 80% of the time that NTCE will be triggered for the next

0 to 15 hours following a trigger of both CL and NLC. However, regarding Table 4, couple (CL, NLC) will only detect 5% of the TC being exceeded. Other associations like WICR and NLC seem to emerge with better results in detecting and predicting NTCE. More work is needed to find the best set of measures.

5 CONCLUSIONS AND PERSPECTIVES

This paper focuses on the evaluation and detection of the machine criticality in the framework of TCT management. To detect critical machines, several criticality measures, static and dynamic, have been adapted from the literature to suit the problem under study, and new criticality measures proposed. These measures have been compared based on industrial data using a simulation-based approach. The findings provided by static and dynamic measures do not always converge. Studying only the static measures is not thus sufficient to conclusively state the criticality of a machine.

Studying the criticality under normal conditions, it appears that measures TWT, NTCE, and DWT are sufficient to estimate if TCs are going to be exceeded in the time range of the simulation. More specifically, measures NTCE and DWT indicate on which machines TCs are being exceeded, while TWT completes the information with machines more likely to be at the origin of TCs being exceeded. However, as the simulation cannot be run forever, other measures have their importance when making a decision. It appears that having measures NLC and CL triggered is likely to lead to a violation of TC in the following hours. Having these measures triggered could also be a sign that more attention needs to be paid to the specific machines at the time they are triggered.

As a perspective, there is always place for improvements for the comparisons of the criticality measures. Some results have been shown in this paper but further research could be done, such as finding the best combination of measures to describe the criticality of the machines or the best detection limit, e.g., by using decision trees. In addition, for the case of the criticality under abnormal conditions, the use of capacity planning machines and scenarios could help in understanding the impact of abnormal conditions on machines and TCTs, adding new perspectives and focus points. Our ultimate goal is to propose and validate in the near future with operators at STMicroelectronics a decision support system that embeds the simulation-based approach presented and other KPIs including the estimation of criticality in terms of TCs.

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