Chaos, AI and the AMHS: An Update on Semiconductor Front-end Fab Logistics

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DURING THE LAST 40 YEARS, FRONT END fabrication fabs have evolved parallel with wafer form-factor developments. Yet basic logistics principles in use have not changed. We move wafer lots through the process one by one, via discrete operators or automated vehicles. This ancient logistics needs to change in light of modern tools available to optimize manufacturing. This review looks at some of the problems.

For clarity we adopt definitions. For DISPATCH: as managing WIP to comply with processing resources. Its objective is optimum throughput/ utilization. And for AMHS: as managing WIP complying with transport and storage resources. Its objective is optimum cycle time. Then, in the following we analyze AMHS, as the executor of fab logistics. We also define MANUFACTURING CYCLE TIME to consist of 1) tool process time, and 2) wafer *inter process transport time*. For each lot. (Where transport time includes and may be segmented and interrupted by storage times.) The domain of this inter process activity is then modeled as *inter process state space.* This *state space model* is the subject of this review. Considering this model as a dynamic system, submitted to modern analysis, and questioned if it may be chaotic or may be improved via machine learning.

AMHS In the inter process state space

AMHS, the Automated Material Handling System, provides the infrastructure for product flow between process tools and storage tools. It enables execution, and planning, of process sequences. Historically, the primary methodology for this inter process sequencing was discrete substrate moves via discrete vehicles or people. A fundamentally limited method, due to its inability to move substrate lots on demand. Yet adopted by industry consortia for today's 300 mm wafer format factories. Few exceptions to this formula exist, in the form of conveyor networks, which liberate wafer flow to be at will, independent of vehicles or people transports.

Recursion of substrate flow, combined with the forever increasing number of mask layers, burdens the AMHS with increased complexity and delivery volume. This results in poor flow factors, meaning that more time is spent by each product being moved then being actually processed. Hence comes the urgency for updating AMHS. Which became a major contributor to factory cycle time and throughput. To keep things in control, forecasting wafer lot moves becomes a necessity, and by *modeling it we aim to predict arrival times and enhance utilization of the processing assets.*

How do AMHS execute product flow? 1) Todays conveyor network type AMHS (with direct equipment Interface) is a simple case. It requires no scheduling of the AMHS system. It provides a route from all tools to all other tools in the form of a network of paths, similar to a NY city street map. Direct carrier placement onto the network with a destination will move the wafer lots autonomously to destination. And at street crossings, the lots are moved FIFO. This simplicity, while still allowing in-flight reassigns of destinations, is achieved via the embedded controls throughout the conveyor tracks. 2) The discrete vehicle type AMHS demands more complexity in logistics. Individual vehicle assignments are made, or planned, as substrates appear at the output of process tools. This demands forecasting in order to maximize vehicle service efficiency and tool utilization. Yet, there is no perfect mathematical solution to this moving vehicle type of distribution system. Thus, various heuristic solutions are in use.

Chaos

We like to model our systems with mathematical formulas. We do this primarily to predict future states of those systems. It is in this forecasting context that the mechanism of Chaos becomes pertinent to dynamic systems. Chaos allows the rapid growth of uncertainty in those mathematical models and thus limits our ability to predict. One condition for chaotic development in dynamic system models is small variation in initial conditions. Where chaos provides us with a description of their rapid growth. Another fundamental condition for the system model is its nonlinearity. So outcomes are not proportional to changes in initial conditions. And lastly, Chaotic system models are deterministic, in the sense that their current state completely determines their future state, i.e. computer models. Do these conditions apply to the formulation of our *state space*: the *inter process wafers lot space*, where AMHS models operate?

Chaos and AMHS methodologies

AMHS systems are physical dynamic systems acting on the *wafer-lot state space* outside of process tools. But we are not modeling AMHS. Instead, we model the *inter process wafer-lot state space comprising of multitudes of wafer lots on the move or in dynamic storage.* Our model is the state space of the inter process moves with parameters of delivery time T_n, velocity V_n, and distance D_n, of each wafer lot. And then define a mathematical map for this which relates delivery time of a wafer lot move to the next process and beyond.

The map on the Conveyor Moves

$$(T_n)_j = \frac{D_n}{V_n} + T_{n-1} + S_n$$

As a wafer lot advances through the manufacturing process its T_n accumulates according to the time series, iterating the steps from tool to tool. Each step starting with the previously accumulated T_{n-1}, and then calculating the next value of T_n. This process is linear, modeling Conveyor logistics as linear dynamic systems. The variance of $\frac{D_n}{V_n}$ and S_n of each move is linearly additive for the final outcome, of total transfer time T of the lot.

Similarly, we model the inter process state space of the wafer lots when discrete vehicle systems are acting on it.

The map via vehical moves

$$(T_n)_j = P(t) + \frac{D_n}{V_n} + T_{n-1} + S_n$$

P(t) being a stochastic vehicle arrival time after request to move.

The probable value of arrival time of a vehicle, after a request-to-move can be modeled as an exponential $P(t) = \lambda e^{-\lambda t}$, where λ would be the shape factor for the exponential probability of t. It may be assigned a value meaning the mean rate of stepping. The point, however, is that the series $(T_n)_j$, is nonlinear as the wafer-lot-moves iterate the formula.

The growth of uncertainty in the cumulative time of wafer lot transits between multiple fabricating processes is subject to exponential growth. This fact is clear, as only the probability of time is inserted in place of T_{n-1} before calculating the newly accumulated time for transits. Then, adding probabilities inside the formula the algebra of probabilities dictates a multiplication (ref. Towards Clean Frontend Manufacturing, *Horn, IEEE Transactions, 2022 CSTIC).* Resulting in exponential growth. This dynamic system, or rather our map imitating it, is chaotic. Meaning, that forward predictions, forecasting arrival times between processes, and cycle time for the lot, have severe limitations. We can only forecast a very near future. Then, to prevent the uncontrolled growth of uncertainty, the wafer lot transfer process itself is sometimes suspended (stockers/buffers) and restarted. Overall, chaotic behavior limits the forecast horizon for the state when moving via discrete vehicle type AMHS.

Machine learning (AI)

How would machine learning operate in the *inter process wafer moves state space*? In the iterative process of observing values of parameters in that space, i.e. observing its *state*, based on which an *action* set is computed by the *agent*, followed by rapid delivery of the *action* to the system (ref. AMHS in the Reinforced Dispatch Learning Environment of IC Fabs. *Horn, Semiconductor Digest*, January 2024) The parameters to observe in the *inter process wafer state space* are the accumulated vectors $(T_n)_j$ resulting from move distances, times for inter process transits and times in dynamic storage. Suggesting routing algorithms to improve over all time T to transit the fabrication process. Such algorithms would comprise the *Agent.* And *Rewards* for learning be calculated for improved average delivery times. By default, a substantial part of learning would be the minimizing of S_j, the stocker times of routes.

Conclusions

There are caveats to this learning process. Such as steady state wafer starts, defined *to-from* process flow tables, and a data base for historic $(T_n)_j$. Then a most serious question is the ability of the Machine Learning scheme to work with the *uncertainty* in the current computations of $(T_n)_j$. As shown above for the discrete vehicle AMHS systems this uncertainty is great. How would the *agent* create an *action* based on uncertainty in the measurement of the *state*?

Nonlinearity of the AMHS models for current 300 mm, and also for the legacy 200 mm fabrication thus represent difficulties for oncoming AI applications. Early demonstrations of AI were applied to Dispatch models which neglected considerations of realistic AMHS. No application of AI for reducing the substrate content (cycle time) in the inter process state space, i.e. the pure AMHS case, are known in literature. But we anticipate that the linearity of conveyor transport nets would offer an easier way for machine learning and so offer a longer horizon for forecasting. And, at the same time, the likelihood of voiding the chaotic growth of uncertainty. Considering the exponential growth of uncertainty of the vehicle model, the wisdom of maintaining our current discrete vehicle based AMHS design, as is, becomes questionable. Installations already exist where the inter process transport assignment of the vehicles is transferred to conveyors, while maintaining the vehicle's vertical service assignments to the tool port.