MANUFACTURING-UBER:
Intelligent Operator Assignment in a Connected Factory

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Abstract: This paper introduces the Manufacturing-Uber concept for dynamic assignment of operators in the Connected Factory. In traditional non-IoT machining environments it is common to assign an operator to a (small) number of machines, clustered in close proximity within a cell. In contrast to “fixed” assignment within a cell, the Manufacturing-Uber approach leverages the connectivity of the IoT environment to allow on-demand “floating” operator assignment across cells. An intelligent assignment engine determines and assigns the operator to achieve best system performance. Results show that Manufacturing-Uber outperforms fixed assignment with respect to reduction in required operators, increased machine up-time and more parts completed.

Keywords: Connected Factory, Intelligent Manufacturing Systems, Cognitive Systems, Operator Assignment, Industry 4.0

1. INTRODUCTION

With the rise of the smart, connected factory, operations both inside and outside the four walls are being transformed from traditional rigid operational processes and standard automation to a fully connected and flexible system—one that can use a constant stream of data from connected operations and production systems to learn and adapt to new demands. The smart factory becomes a flexible system that can self-optimize performance across a broader network of connected entities—machines, people, robots, and others. As the capabilities and technologies move further towards the Industry 4.0 vision, the flexible system can self-adapt to and learn from new conditions in real or near-real time, and autonomously run entire production processes. Smart factories can be implemented within the four walls of the factory, but they can also connect to a global network of similar production systems, and even to the digital supply network more broadly in a completely distributed system.

Integration of the physical environment of machines and factories with the virtual world is enabled by the application of cognitive computing and data science to the operational management of the manufacturing enterprise. As more and more entities on the manufacturing floor are embedded with sensors, actuators and computational power, today’s centrally controlled manufacturing environment will give way to a new system capable of self-management and self-organization. In this manufacturing future, each entity, whether machine or robot or part, is self-aware and able to make decisions autonomously and in concert with other entities. At the core of this vision is the notion of cyber-physical systems—systems composed of physical objects or entities that have embedded software and computing power that blend the physical and virtual to move towards self-aware manufacturing (Lee et al., 2014; Shariatzadeh et al., 2016).

A lot has been written about the potential benefits of the Connected Factory and IoT as industry moves in this direction. There is, however, a need for a deeper understanding of how the various operational processes can be implemented within this environment, what the realized operational benefits will be, and how to create a roadmap for moving to a system of distributed machining operations in an Internet-of-Things environment (Zhang et al, 2017). In this paper, we explore the operator assignment problem in a connected factory environment. We develop and simulate an IoT-enabled system for the assignment of operators in a cellular machining environment that leverages the connectivity of IoT with an intelligent assignment engine that matches floating operators and self-aware machines for improved allocation of manufacturing resources.

A number of researchers have addressed the problem of worker assignment to achieve specific goals. Azizi et al. (2010) address worker assignment to reduce boredom and increase skill variation. Others have focused on matching assignments with worker skills and proficiency levels (Lian et al., 2018). Madhavi et al. (2010) modelled production planning considering worker availability and skill levels for cellular manufacturing systems in a dynamic environment. The problem of assigning jobs to operators that work on a non-fixed position and, instead, "float" or rotate among different machines or stations has been studied by Gebennini et al. (2018) with a focus on increasing system efficiency by minimizing travel times from station to station and reducing injuries and sick leave. Niakan et al. (2016) proposed a Dynamic Cell Formation approach in which the worker's assignment, environmental and social criteria are considered in worker assignment in an Industry 4.0 environment.

2. THE MANUFACTURING-UBER (M-UBER) CONCEPT

2.1 Concept Introduction

As a first step towards this vision on intelligent manufacturing in a Connected Factory, we propose Manufacturing-Uber (or M-Uber)—a concept that leverages the embedded connectivity and computational capabilities among various entities on the shop floor (machines, devices, people, etc.), along with remote wireless interconnectivity, to dramatically expand operational capabilities. In the case of M-Uber, this data serves as input to an intelligent assignment engine with cognitive computing capabilities that delivers business value through increased manufacturing throughput, higher yields, improved efficiency and reduced downtime.

Like the taxi-hailing web app, M-Uber brings on-demand assignment to the manufacturing shop floor allowing real-time job scheduling and process control. Computer numerically-controlled (CNC) machining is largely automated with only periodic tasks that require operator intervention, such as tool changes, part loading/unloading, etc. It is common practice to have an operator oversee more than one machine simultaneously. The traditional approach is to assign one operator to two (or perhaps three) machines in a cell. That operator is responsible for serving only those machine interventions within his/her assigned cell.

As an extension to this paradigm, we propose a new approach, realized in a mobile software application, that enables Uber-type oversight of all machines in a production facility by a collection of operators, none of which are assigned to a particular machine or group of machines. In this scenario, each machine is equipped with sensors that enable real-time self-reporting of their state of operations to a cognitive computing engine that sends an alert when operator intervention is required. The cognitive engine can assign an operator based on geographic proximity to the machine in question (and, therefore, the travel time), other pending interventions, estimated time for the selected intervention, and the operator skill set that matches the reported machine diagnostics. These alerts and assignments will be digitally distributed (e.g., by smartphone) to the assigned operator.

Over time, the cognitive engine is capable of "learning" dynamic patterns of part production on the shop floor (e.g. chip making in machining operations), machine availability and wear, and anticipation of needed interventions. Operators will be selected based on "learned" intelligence about their demonstrated skills. To track operator location, radio frequency identification (RFID) tags can be embedded in a name tag, for example. The operator skill set will be archived in a database that is part of the software application. The operator availability will be set by monitoring his/her status through responses to other queries. Similar to Uber, the most feasible "driver" (operator) will be requested and the call will either be accepted or rejected. If rejected, the next best operator will be contacted. In this way, operator efficiency can also be tracked and reported.

2.2 Motivating Example

The M-Uber concept is demonstrated in Figure 1. In the left panel, the traditional approach of one operator-to-two machines is depicted for six total machines. In the middle panel, the M-Uber concept is implemented in a single cell, again with three operators. In the right panel, after the distributions of machine usage have been studied, the M-Uber solution was found to be two, rather than three, operators. In the figure the machines are blue and hatched if an operator intervention is required. They are white without hatching if operational (making chips). The operators' spatial location is identified by the position of the indicator (circle with operator number). The indicator is unfilled if the operator is idle and filled if engaged. For the traditional "fixed" assignment approach (left), operators 1 and 2 are idle for the selected intervention state; operator 3 is only able to service one machine while the other assigned machine waits until the first intervention is completed. For M-Uber (middle), operators are no longer restricted to specific machines but float within their assigned cell. Operator 1 remains idle, but floating operators 2 and 3 are free to service the two required interventions. Under "floating" M-Uber the number of required operators is matched to the intervention rate (on average) and operator productivity is increased.

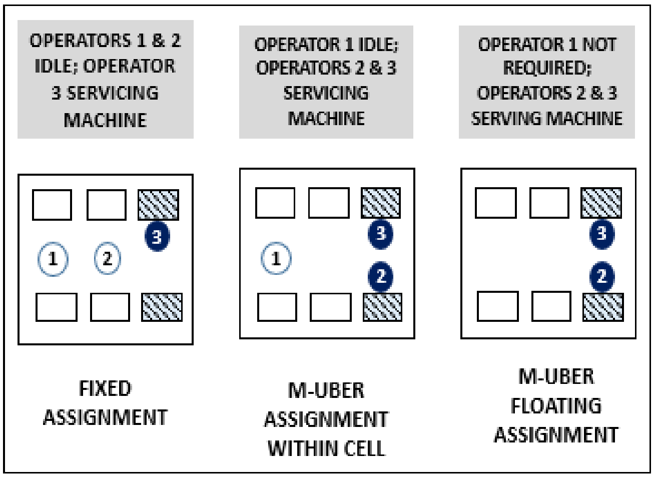

Fig. 1. Illustration of M-Uber Advantage

Fixed assignment of operators is typically utilized in factories so that operators can stay within visual distance of the machines for which they are responsible. Thus, an operator is able to “see” when a machine requires intervention and respond accordingly. Operators are typically assigned to one or more machines depending on the frequency of required interventions and the physical distance of the machines from the operator so they can quickly respond.

With M-Uber, operators are not limited to a single machine cell. This eliminates two scenarios that decrease factory efficiency in the fixed assignment scheme: 1) operator idle while no machines in the cell require intervention; and 2) service delays when more than one machine assigned to an operator in the cell requires intervention. In the first case, the operator is not needed at that time (operator idle). In the second, both machines will be waiting and one will be idle longer than necessary because the operator can only service one at a time. With conversion to the “floating” operator concept and the support of a “smart” assignment tool, M-Uber offers the potential for improved responsiveness to machine stoppages, a corresponding increase in machine usage, and optimization of the number of required operators.

The advantages of the M-Uber concept include:

Reduced Machine Downtime. Since most modern factories run 24x7 to keep their operating costs competitive, time lost due to machine downtime can have a significant impact. Optimally, downtime can be anticipated and avoided through condition-based maintenance. When downtime cannot be anticipated, M-Uber allows problems to be addressed immediately. M-Uber results in better asset utilization and improved throughput.

Reduced Operators Needed. Traditionally, one operator is assigned to two (or perhaps more) machines in a cell. S/he is then responsible for serving only those machine interventions within his/her cell to ensure that the machines produce quality parts at the highest possible rate. Under M-Uber, the number of operators, and this idle time, is reduced without compromising machine uptime. M-Uber results in reduced operator costs and improved scheduling.

Matching of Operator Skills to Needed Intervention. Operator capabilities to successfully implement interventions vary according to experience and problem-solving skills. When operators are dedicated to specific machines, operators may not have the best skills to address the problems that occur in the assigned cell. M-Uber allows the flexibility to assign operators to problems based on skill and experience. This also helps to minimize the impact that absenteeism and operator turnover have on production.

3. SIMULATION ENVIRONMENT

We model a cellular manufacturing environment consistent with a typical aerospace parts manufacturer producing high-precision, high-cost, high-volume parts for an OEM jet engine manufacturer. Our research and experimental design was motivated by a large OEM aerospace manufacturer that fabricates fan blades and other rotable parts for turbofan jet engines. These parts are machined, i.e. cut, from titanium blocks by computer-numerically-controlled cutting machines. Each part requires approximately four hours to achieve final form—removing excess material from a block of raw material using diamond cutting tools. The cutting force and path are programmed to provide the right geometry part with tight tolerances and high surface finish. Titanium is one of the hardest materials to machine, and the diamond cutting tools need to be replaced often by operators.

3.1 Manufacturing Environment

The simulation environment, shown in Figure 2 and consistent with the target company, includes four machining cells, each with six identical cutting machines—totalling 24 machines. All the machines are capable of producing the same single titanium part for a jet engine by machining to meet target tolerances and surface finish. The factory runs 24 hours per day—equivalent to 10,080 minutes per week. No changes of shifts are implemented in the simulation which runs continuously for 7 days.

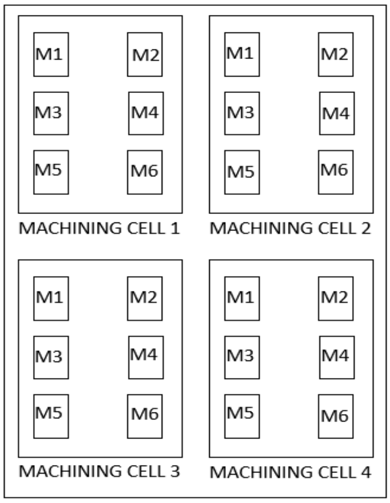

Fig. 2. Cellular Manufacturing Simulation Environment

3.2 Operator Interventions

The simulation models four operator interventions to events on the factory floor. Human operators respond to specific events, c.f. intervene, on the factory floor to make sure that the machine tools continually perform at a high level to minimize downtime. We have generalized the types of events that may require intervention into four event types.

Event Type 1: Tool change. Because of the hardness of titanium, cutting tools must be replaced frequently by the operator. As the tools become dull, they start to “chatter” which signals to the operator that the tools must be changed. Tools are changed frequently during machining, typically on a prescribed schedule, to avoid chatter. The machine is not operational during tool changes.

Event Type 2: Part Changeover. After a part has been completed, the operator must remove the completed part and set-up a new titanium blank in preparation to machine the next part. The machine is not operational during part changeover.

Event Type 3: Low-level corrective maintenance. During normal operations, a number of corrective or preventive maintenance operations may be performed. For example, adjustments may need to be made to the tool to correct for any deviations from the prescribed cutting path. Or oil pressures may fall triggering a machine stop requiring fluid adjustments to prevent a more serious breakdown. The machine is not operational during corrective maintenance.

Event Type 4: High-level breakdown maintenance. Infrequently, a serious unpredicted maintenance problem is encountered. The machine breaks for a reason that is not known and can no longer perform its function until it is repaired. This type of event may take more time to diagnose and fix, and may require additional skill or training. The machine is not operational during breakdown maintenance.

3.3 Intelligent Assignment Engine

Under M-Uber assignment, the task of assigning the "best" operator falls to an intelligent assignment engine that uses local and global information, as available and relevant to the assignment rule, to match operators with events that need intervention (c.f. tool change, set-up, low-level maintenance and high-level maintenance). When an event occurs, and there is only one operator available, that operator is assigned to that machine. When an event occurs and there is more than one operator available, the engine controller uses a "shortest distance" policy to assign the "best" operator.

The engine controller calculates the walking times for all available operators to reach the event and assigns that operator who is the closest. In highly stressed shop floor operating regimes, more events may be occurring than available operators. In this case, the machines go into a queue waiting for assignment of the next "available" operator. Once in a queue, the intelligent assignment engine can use different policies to assign operators to machines, as the operators become available. In this paper, the controller implements a "first-in first-out" scheduling policy.

3.4 Operator Assignment Rules

In this paper we compare two simple operator assignment policies: traditional fixed operator assignment and M-Uber floating operator assignment.

Traditional (i.e. Fixed) Assignment. Each cell of 6 machines has 3 operators, each of which is assigned to two machines as shown in Figure 1 above. Machines are "dumb" and not networked. Since operators are "fixed" they are also not networked and their location on the factory floor is assumed to be confined to a particular cell. An operator must visually assess the operational state of the machine which requires physical proximity in order to observe its current operational state (c.f. functioning, chatter, warning lights, etc.). The operator can only service one machine at a time. If the second machine requires attention while the operator is intervening with respect to the first machine, the second machine must wait until the operator has completed the intervention on the other machine.

M-Uber (i.e. Floating) Assignment. Operators are allowed to "float" among any of 24 machines on the factory floor as needed (6 machines in 4 cells of the simulation). Machines are "aware" and networked in an IoT environment. Similarly, operators are "networked" and their location on the factory floor is visible and can be tracked in real time. Machines are aware of their operational status in real time, that is they know whether they are capable of working or not and can convey that information to a central controller. In addition, when they break, they are able to convey to the network the type of event (c.f. event types 1-4) that caused them to stop operating. Operators can only service one machine at a time. However, if an operator is available (i.e. idle), and a machine in another cell requires an intervention, that operator can move to that machine regardless of location on the floor, if the central controller determines that operator is the "best" operator to assign.

4. EXPERIMENTAL DESIGN

During the simulation, operators are matched with machine events, as described above, that require intervention based on either fixed assignment or M-Uber assignment. The occurrence of each of the above four event types (tool change, part changeover, low-level corrective maintenance and high-level breakdown maintenance) is described by a distribution with mean, standard deviation, minimum and maximum values.

The *event frequency* is defined as the time between subsequent events of the same kind. For example, cutting tools need to be changed on order every 10 minutes, so the event frequency would be 10 minutes between subsequent tool change events. The *event duration* is defined as the length of time that an event can be expected to last. For example, if it takes 3 minutes to replace a cutting tool, then the specified event duration is 3 minutes.

The event frequency reflects the number of events occurring for each machine; machines with a high number of events demand more operator interventions. Event duration is a proxy for the time is takes an operator, once assigned to a machine, to intervene and return the machine to full operation. In practice, the values of event duration and event frequency can be estimated based on actual factory data. The parameter values will vary depending on the characteristics of the factory. In this case, we have estimated these values based on real-time data collected by the aerospace company.

We also define three levels of operational intensity (100%, 75%, and 50%) to reflect the frequency of demand of events requiring operator intervention. Operational intensity will vary, across manufacturing environments, depending on the type of machining process, type of material being machined, and the reliability of machinery.

Distribution parameters for the three levels of operational intensity for event frequency are provided in Table 1 to include mean, standard deviation, minimum and maximum values.

Table 1. Event Frequency Distribution Parameters

Event Frequency at 100% Operational Intensity				
Event Type	Mean	St Dev	Min	Max
Tool Change	16	2	11	21
Part Changeover	240	5	235	245
Low-Level maintenance	90	30	40	140
High-Level Maintenance	1500	500	1000	2000

Event Frequency at 75% Operational Intensity				
Event Type	Mean	St Dev	Min	Max
Tool Change	20	2	15	25
Part Changeover	240	5	235	245
Low-Level maintenance	135	30	85	185
High-Level Maintenance	1875	500	1375	2375

Event Frequency at 50% Operational Intensity				
Event Type	Mean	St Dev	Min	Max
Tool Change	24	2	19	29
Part Changeover	240	5	235	245
Low-Level maintenance	180	30	130	230
High-Level Maintenance	2250	500	1750	2750

Distribution parameters for event duration are provided in Table 2 to include mean, standard deviation, minimum and maximum values. The distribution parameters for duration are the same for all three levels of operational intensity.

Table 2. Event Duration Distribution Parameters

Event Duration at 100%, 75%, 50% Operational Intensity				
Event Type	Mean	St Dev	Min	Max
Tool Change	3	0.5	2	4
Part Changeover	10	3	6	14
Low-Level maintenance	10	2	8	14
High-Level Maintenance	90	10	60	120

5. SIMULATION RESULTS

Simulations were performed for both the fixed assignment and the M-Uber assignment scenarios. Comparative results of the experiments are described in the sections below. Metrics of interest include: 1) the number of required operators and the total number of parts machined over the simulation period by those operators, 2) the increased machine up-time, and 3) the machine wait times for the four event types.

5.1 Increased Production with Fewer Operators

One of the advantages of M-Uber is the potential reduction in labor costs due to the need for fewer operators to achieve the same output under fixed assignment. Figure 3 illustrates, for the cases of 100%, 75% and 50% operational intensity, the reduction in the number of operators needed to match production levels under fixed assignment. For comparison, the number of parts produced under fixed assignment is indicated by the horizontal line. As shown in Figure 3, eight (8) operators working under M-Uber rules can produce the same number of parts as twelve (12) operators working under fixed assignment rules for the three levels of operational intensity studied. Further, the same twelve (12 operators), under M-Uber policy, can produce 7% more parts in a highly stressed factory (100% operational intensity) and 3% more parts in a lightly stressed factory (50% operational intensity). When the number of operators falls below eight (8), M-Uber does not outperform a fixed assignment with 12 operators where each operator is assigned two machines.

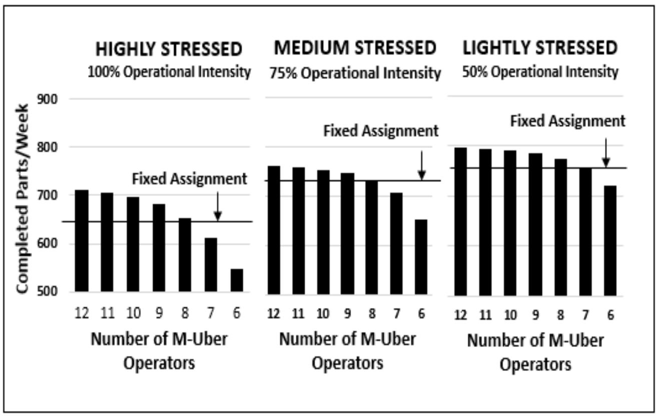

Fig. 3. Total Parts Complete

5.2 Increased Machine "Up-Time"

Table 3 illustrates the percent increase in the total time per week that all 24 machines on the factory floor remain operational. Machine "up-time" is defined as the total number of minutes out of 10,080 total weekly minutes that all of the machines are working. This time does not include time spent waiting for an operator to intervene and the time spent servicing the machine. Results are presented for all three levels of operational intensity. As shown in Table 3, for 100%, 75% and 50% operational intensity, respectively, the increase in machine "up-time" per week is 7.3%, 5.3% and 4.4%. The areas in gray in the table indicate the breakpoint with respect to number of operators below which M-Uber does not perform better than fixed assignment.

5.3 Reduced Machine Wait Time

Reductions in machine down time under M-Uber can be attributed to the increased availability of floating operators who are not constrained to a particular cell but are able to float between cells. Table 4 provides the total wait times per week per event type. We expect different wait times across events since their frequencies and durations vary. Machine wait time is computed as the total number of minutes out of 10,080 total weekly minutes that each machine waits for an operator to be assigned for an intervention. Table 5 provides the increase in the number of events that are able to be serviced under M-Uber compared with fixed assignment. The non-shaded areas in both figures indicate the combination of event type and operator number for which M-Uber outperforms fixed assignment.

Table 3. Comparison of Machine Up-Times

Policy	Number of Operators	Operational Intensity: 100%	75%	50%
		Percent of Time Machine in Operation per Week (%)		
Fixed	**12**	**65.9%**	**71.8%**	**75.7%**
Floating	12	70.7%	75.6%	79.0%
Floating	11	70.1%	75.3%	78.7%
Floating	10	69.2%	74.7%	78.5%
Floating	9	67.8%	74.1%	77.9%
Floating	8	64.9%	72.8%	76.8%
Floating	7	60.8%	70.1%	75.2%
Floating	6	54.4%	64.8%	71.4%

Table 4. Comparison of Service Wait Times (100% Operational Intensity)

Policy	No. of Operators	Tool Change	Part Complete & Set-Up	Low-Maint.	High-Maint.
		Time (minutes)			
Fixed	**12**	**15,278.15**	**1,081.46**	**2,634.93**	**168.27**
Floating	12	2,732.29	285.32	472.36	28.71
Floating	11	4,044.25	438.72	711.90	44.82
Floating	10	6,342.36	704.24	1,147.53	55.70
Floating	9	10,037.75	1,093.05	1,752.63	112.40
Floating	8	17,261.60	1,873.83	3,113.08	194.54
Floating	7	28,645.90	2,698.64	5,086.84	320.51
Floating	6	45,840.56	4,125.65	8,305.88	428.63

Table 5. Number of Service Interventions (100% Operational Intensity)

Policy	No. of Operators	Tool Change	Part Complete & Set-Up	Low-Maint.	High-Maint.
		Events (number)			
Fixed	**12**	**9,966**	**650**	**1,761**	**95**
Floating	12	10,675	696	1,887	98
Floating	11	10,594	696	1,870	98
Floating	10	10,460	689	1,848	98
Floating	9	10,243	672	1,811	96
Floating	8	9,813	647	1,736	93
Floating	7	9,193	600	1,622	85
Floating	6	8,227	533	1,451	73

6. CONCLUSIONS

The business impact of M-Uber, once matured, will be significant. It can be implemented in any manufacturing facility that uses networked CNC equipment; the domain includes aerospace, automotive, medical, heavy equipment, etc. M-Uber reduces the required number of operators, and thus labor costs, while simultaneously enabling a quantitative method for assessing operator productivity. It increases machine utilization, which results in higher part counts and, therefore, greater productivity and profit. Further, by continually monitoring machine status, it will serve as a "big data" resource for preventive maintenance to anticipate trends in machine performance that required intervention. Extensions of this research include the incorporation of different operator skill levels and "learning" in the assignment of operators. More complex job sequencing policies beyond first-in first-out are also being explored to improve the overall efficiency of M-Uber operations.

The cognitive computing capabilities that enable M-Uber to intelligently balance machine availability and work flows in cells, and to process and negotiate the scheduling of competing events across the shop floor, can be scaled to the enterprise level—given that correct information is available at the right time for the right purpose and to the right person/machine for optimal decision-making. As more software and embedded intelligence are integrated into other assets on the factory floor such as robots—as well as entities across the supply chain—cognitive computing and other data science technologies will further integrate functional intelligence from the operational manufacturing level into higher-level enterprise processes.

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