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 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 this “fixed” assignment, 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, Worker Assignment, Industrie 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 fixed 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 Industrie 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 operate 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.

A lot has been written about the potential benefits of the Connected Factory and IoT as industry moves in this direction. There is 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. In this paper, we explore the worker assignment problem in a connected factory environment. We develop and test 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 to match floating operators and self-aware machines.

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 traveling 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 Industrie 4.0 environment.

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

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 and exponentially increase the volumes of data generated. In the case of M-Uber, this data provides input to a cognitive computing engine that delivers business value through increased manufacturing throughput, higher yields, improved efficiency and reduced downtime.

Like the taxi-hailing web app, M-Uber brings to the manufacturing shop floor on-demand assignment with dynamic pricing and real-time 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 will 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 text message) to the assigned operator via smartphone.

Over time, the cognitive engine will “learn” 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.

2.1 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 (three operators). In the middle panel, the M-Uber concept is implemented, again with three operators. In the right panel, after the distributions of machine usage have been studied, the optimized result 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), it is observed that operators 1 and 2 are idle for the selected intervention state; operator 3 is only able to service one machine, while the other machine must wait until the first intervention is completed. For M-Uber (middle), operators are no longer restricted to specific machines. In Figure 1, operator 1 remains idle, but floating operators 2 and 3 are free to service the two required interventions. After optimization (right), M-Uber has matched the number of required operators to the intervention rate (on average) and operator productivity is increased.

![Fig. 1: Illustration of M-Uber Advantage](image)

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 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 is optimized to reduce idle time by operators 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. OPERATOR ASSIGNMENT POLICY

#### 3.1 Assignment Policies

In this paper we compare two simple operator assignment policies: the traditional fixed operator assignment and the M-Uber assignment policy. M-Uber policies are enabled by the real-time awareness in an IoT environment of the current operational state of the machine (operational or needing intervention), as well as the current and future assignments of each operator and the operator’s location on the factory floor.

#### 3.2 Fixed Operator Assignment

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.

### 3.3 Floating M-Uber Assignment Policy

Under the 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 policy, 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 operating regimes, there may be more events occurring at approximately the same time as there are 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 rules to assign operators to machines, as the operators become available.

### 4. SIMULATION ENVIRONMENT

We model a cellular manufacturing environment patterned after 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 rotatable 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 machine to final specifications—removing excess material from a block of raw material using cutting tools. The cutting force and path are programmed to provide the right geometry part with tight tolerances and high surface finish. Each part requires approximately four hours to achieve final form. Titanium is one of the hardest materials to machine, and the diamond cutting tools need to be replaced often by operators.
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 fixed within the 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 Policy.*

Under the M-Uber assignment policy, operators are allowed to “float” among any 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.

5. EXPERIMENTAL DESIGN

During the simulation, operators are matched with machine events, as described above, that require intervention based on either a fixed or M-Uber policy. The occurrence of each of the above four event types (tool change, set-up, 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 it takes a worker, 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 Type              | Mean | St Dev | Min | Max |
|-------------------------|------|--------|-----|-----|
| Tool Change             | 16   | 2      | 11  | 21  |
| Part Set-Up             | 240  | 5      | 235 | 245 |
| Low-Level Maintenance   | 90   | 30     | 40  | 140 |
| High-Level Maintenance  | 1500 | 500    | 1000| 2000|

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 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  | 1870 | 500    | 1375| 2375|

6. SIMULATION RESULTS

Simulations were performed for both the fixed assignment policy and the M-Uber assignment policy. 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.

6.1 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 policy. Figure 3 below illustrates, for both the case of 100% operational intensity and 50% operational intensity, the reduction in the number of operators needed to match production levels under a fixed policy. For comparison, the number of parts produced under a fixed assignment policy is indicated by the horizontal line. As shown in Figure 3, eight (8) operators assigned using M-Uber can produce the same number of parts as twelve (12) operators operating under a fixed assignment policy. Further, the same twelve (12 operators) 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.

Figure 4 below 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 Figure 4, 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.

6.3 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. Figure 5 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. Figure 6 provides the increase in the number of events that are able to be serviced under M-Uber compared with a fixed policy. The non-shaded areas in both figures indicate the combination of event type and operator number for which M-Uber outperforms a fixed policy.

| Policy | Number of Operators | Percent of Time Machine In Operation per Week (%) |
|--------|---------------------|--------------------------------------------------|
| Fixed  | 12                  | 100% 65.9% 71.8% 75.7%                          |
| Floating 12 | 12                  | 100% 70.7% 75.6% 79.0%                          |
| Floating 11 | 11                  | 100% 70.1% 75.3% 78.7%                          |
| Floating 10 | 10                  | 100% 69.2% 74.7% 78.5%                          |
| Floating 9  | 9                   | 100% 67.8% 74.1% 77.9%                          |
| Floating 8  | 8                   | 100% 64.9% 72.8% 76.8%                          |
| Floating 7  | 7                   | 100% 60.2% 70.1% 75.2%                          |
| Floating 6  | 6                   | 100% 54.4% 64.8% 71.4%                          |

Fig. 4: Increased Machine Up-Time Under M-Uber

| Policy | No. of Operators | Tool Change | Part Complete & Set-Up | Low-Maint. | High-Maint. |
|--------|------------------|--------------|-------------------------|------------|-------------|
| Fixed  | 12               | 15,278.19    | 1,081.46                | 2,634.93   | 168.27      |
| Floating 12 | 12               | 2,732.29     | 285.32                  | 472.35     | 28.71       |
| Floating 11 | 11               | 4,044.25     | 438.72                  | 711.90     | 44.82       |
| Floating 10 | 10               | 6,342.36     | 704.24                  | 1,147.53   | 55.70       |
| Floating 9  | 9                | 10,037.75    | 1,093.05                | 1,752.63   | 112.40      |
| Floating 8  | 8                | 17,261.60    | 1,873.83                | 3,113.08   | 194.54      |
| Floating 7  | 7                | 28,645.90    | 2,698.64                | 5,086.84   | 320.51      |
| Floating 6  | 6                | 45,840.56    | 4,125.65                | 8,305.88   | 428.63      |

Fig. 5: Reduced Service Wait Times under M-Uber

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

Fig. 6: Increased Number of Service Interventions

7. M-UBER AND THE EXTENDED MANUFACTURING ENTERPRISE

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. Cognitive computing technologies and data science tools will be capable of spanning the entire extended enterprise, detecting “invisible” problems and avoiding unscheduled downtimes before system failure.

8. CONCLUSIONS

The business impact of M-Uber, once matured, will be significant. It can be implemented in any manufacturing facility that uses CNC equipment; the domain includes aerospace, automotive, medical, heavy equipment, etc. It will minimize operator costs through its personnel optimization capability, while simultaneously enabling a quantitative method for assessing operator productivity. It will increase machine usage, which will result in higher part counts and, therefore, greater productivity and profit. Further, by continually monitoring machine status, it will serve as a “big data” resource that will contribute to preventive maintenance through trends in machine performance and required interventions.

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