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HUMAN ACTIVITY RECOGNITION AND MOBILE SENSING FOR CONSTRUCTION SIMULATION

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ABSTRACT

Construction industry has been constantly lagging behind in terms of efficiency and productivity growth. Simulation modeling can be used to improve the productivity of construction workflow processes through modeling uncertainties and stochastic events that may negatively impact project cost and schedule. In the research presented in this paper, mobile sensors coupled with machine learning techniques are used for ubiquitous data collection and human activity recognition (HAR), which will constitute the key input parameters of process simulation modeling. To assess the designed methodology, an experiment is carried out which replicates a warehouse quality control operation. Smartphones mounted on human bodies are used to collect multi-modal time-motion data. Support vector machine (SVM) is then applied to classify workers' and inspectors' activities, and activity durations are subsequently extracted. Finally, a simulation model is built using the output of the HAR phase and rigorously validated and used to analyze workflow processes, productivity, and bottlenecks.

1 INTRODUCTION

Despite its large footprint in the global economy, the construction industry has been traditionally lagging behind in productivity growth (U.S. Department of Commerce 2014). A key obstacle to achieving high productivity is that most construction projects occur in uncertain, dynamic, and transient environments. As a result, deviations from plans are very frequent, and many planning-phase assumptions render invalid once the actual work starts (Akhavian et al. 2015b), causing rework, delays, and cost overruns. Research has shown that traditional approaches to work progress analysis often fail to effectively and accurately identify key performance indicators (AbouRizk 2010). More recently, computer simulation has gained credibility due to its unique capability to model uncertainties and stochastic events (Akhavian et al. 2015b). In particular, simulation models representing various field processes can be used to improve work plans, optimize resource allocation and utilization, minimize costs or project duration, and increase overall project efficiency (AbouRizk 2010).

To achieve the best results from simulation, the model and inputs should accurately represent the real process (Gong et al. 2009). This requires a significant amount of time and resources to be spent on data collection for simulation input modeling. While being practically inefficient, the technical knowledge and training needed for manual data collection is also substantial and often beyond the common skill pool of construction practitioners. For this reason, automated data collection using sensors, RGB cameras, laser scanners, and inertial measurement units (IMUs) has become more relevant to construction applications. In this study, the authors designed and tested a methodology to use smartphone's built-in IMU sensors for multi-modal time-motion data collection from field workers. Machine learning, specifically, multi-class support vector machine (SVM) algorithm is used for human activity recognition (HAR) from sensor data,

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and activity duration and frequency information are subsequently extracted. This information is then transformed into input parameters for a discrete event simulation (DES) model. Finally, several iterations of the data-driven simulation model are run to analyze crew productivity as well as to optimize workflow processes.

2 LITERATURE REVIEW

There is a strong body of work highlighting the added value of simulation in the construction domain. Among others, previous work has explored simple on-site assessments (McCahill et al. 1993), modeling uncertainties due to factors such as weather (Carr 1979) , evaluating cost distribution and budgeting (Lai et al. 2008), reducing physical demands and controlling fatigue (Seo et al. 2016), and dealing with effects of temporal work space variability on planning (Akinci et al. 2002). Traditionally, expert judgments and historical datasets are the basis for estimating input data for a simulation model. However, in a complex system, relying on personal intuitions can yield unrealistic results and model drifts (Akhavian 2015). Alternately, to achieve more accurate results, simulation input data can be linked to and extracted from remotely distributed sensing devices on the jobsite. Among various types of sensors, wearable (i.e. mobile) sensors are being increasingly used for their ubiquity, affordability, unobtrusiveness, and ease of use (Chen et al. 2011). HAR using wearable sensors has been researched intensively in fields such as elderly care (Jin et al. 2012) and sports (Avci et al. 2010). The idea of coupling machine learning and HAR has been explored more recently in construction (Golparvar-Fard et al. 2011; Yang et al. 2014). Akhavian and Behzadan (2015a) expanded the use of HAR and machine learning to extract activity durations for simulation input modeling. Building on past works, in this study, SVM is used for HAR and activity duration extraction for simulation input modeling. In particular, the aim of this research is to alleviate the need to collect large volumes of data, by investigating whether a relatively small batch of experimental data can be effectively used to conduct rigorous workflow analysis using DES.

3 THE WAREHOUSE OPERATION EXPERIMENT DESIGN

To demonstrate the designed methodology, a warehouse operation experiment is conducted. The goal of this operation is to transport an item (i.e. box) from a loading area to an inspection area, and if accepted, move it further through the system to a designated unloading area. As shown in Figure 1, the operation starts with a worker loading a box into a cart and pushing it to the inspection area. Next, an inspector lifts and inspects the box while the worker is waiting in the inspection area. After inspection, the inspector either accepts or rejects the box. Upon acceptance, the worker lowers the box onto the cart, pushes it to the unloading area, unloads the box and then pulls back to the loading area with the empty cart. If the box is rejected, however, the worker directly pulls back to the loading area with the empty cart. This operation is performed for a total of 30 cycles. To collect data, two smartphones are mounted on each person's body- one on the upper arm and another on the waist. Data are collected from the accelerometer, linear acceleration, and gyroscope sensors.

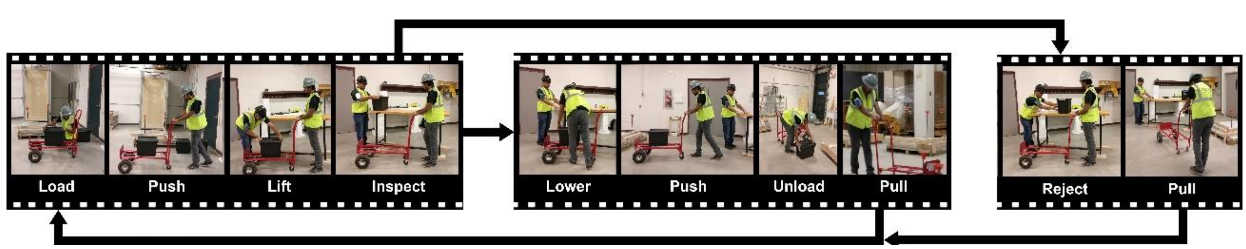

Figure 1: The warehouse operation cycle.

4 DURATION EXTRACTION FOR HUMAN ACTIVITY RECOGNITION

From the collected raw data, jerk (time derivative of acceleration), and magnitude of tri-axial data are calculated (Anguita et al. 2013). Similar to past research (Akhavian et al. 2015a), to have a continuous and orderly data stream, raw and extracted data (jerks and magnitudes) are processed into 180-Hz uniform time series by removing redundancies and interpolating missing data. Processed data are segmented into 2-second windows (360 data points) with 50% overlap, key statistical features for each window are calculated, and each window is labeled with the proper activity class. To identify distinctive data features, ReliefF is applied to training data. Next, 5-fold cross-validation with SVM is applied using the first nth (n = 15 to 576) ranked features. It is found that the first 125 ranked features yield the highest accuracy for classifying the worker's activities, while the first 84 ranked features give best results for classifying the inspector's activities. A Summary of the data preparation process is shown in Table 1.

Table 1: Summary of the data preparation process.

Category	**Summary**
Collected Sensor Data	Accelerometer (X, Y, Z), Linear-Accelerometer (X, Y, Z), Gyroscope (X, Y, Z)
Extracted Sensor Data	Accelerometer-Jerk (X, Y, Z), Linear-Accelerometer-Jerk (X, Y, Z), Gyroscope-Jerk (X, Y, Z), Accelerometer-Magnitude, Linear-Accelerometer-Magnitude, Gyroscope-Magnitude, Accelerometer-Jerk-Magnitude, Linear-Accelerometer-Jerk-Magnitude, and Gyroscope-Jerk-Magnitude.
Sampling Rate	180Hz after processed into time series of uniform interval.
Window Size	360 data points (2 seconds)
Statistical Features	Mean, Maximum, Minimum, Standard Deviation, Mean-Absolute Deviation, Interquartile Range, Skewness, Kurtosis, Autoregressive Coefficients.
No. of Extracted Features	576
No. of Selected Features	125 for Worker, 84 for Inspector
Feature Selection Algorithm	ReliefF
Classifier Algorithm	Multi-class Support Vector Machine

The entire dataset is divided into 3 parts, each containing 5 work cycles for each worker-inspector pair. In 3-fold, each part is used as test data, with the other two being the training data. For each fold, a classifier model is built using multi-class SVM and the annotated training data. Next, the model is applied to test data to predict activities. Predicted results from all three folds are then combined. Classifier confusion matrices are given in Figure 2, which shows that almost all activities are predicted with >80% accuracy.

An activity instance is defined as a group of successive windows classified with the same label. The duration of an instance is calculated by counting the number of windows in that group. A false detection (FD) (a.k.a. outlier) is defined as an instance spanning over only one window, and is treated before duration extraction. Next, statistical distributions are fitted to durations of all instances of an activity. Table 2 compares the sum of actual and predicted durations for each activity. It is seen that with one exception (activity 'Reject'), extracted durations are within ~20% of true values. Potential reasons behind the failure of classifier algorithm to accurately detect 'Reject' are that it 1) had a fast pace and thus very few training data samples (few instances), and 2) was in between the transition of 'Inspect' and 'Wait', resulting in it being confused with these activities.

Worker

	Wait	Load	Unload	Lower	Push	Pull
Wait	93.6%	1.2%	0.0%	1.6%	2.5%	1.2%
Load	0.9%	85.9%	1.4%	0.5%	4.7%	6.6%
Unload	0.7%	0.7%	73.7%	3.6%	15.3%	5.8%
Lower	6.6%	0.7%	1.3%	82.1%	4.6%	4.6%
Push	0.3%	1.1%	1.0%	0.5%	95.9%	1.1%
Pull	0.8%	0.3%	0.7%	0.3%	0.7%	97.3%

Inspector

	Wait	Lift	Inspect	Reject
Wait	99.4%	0.2%	0.4%	0.1%
Lift	22.4%	70.1%	7.5%	0.0%
Inspect	2.8%	2.0%	95.0%	0.2%
Reject	22.2%	3.7%	37.0%	37.0%

Figure 2: Confusion matrices of the classifier's predictions.

Table 2: Comparison of actual and predicted activity durations.

Activity Parameter	**Worker**						**Inspector**			
	Wait	**Load**	**Unload**	**Lower**	**Push**	**Pull**	**Wait**	**Lift**	**Inspect**	**Reject**
Actual Duration (sec)	602.1	200.4	135	154.6	617.1	753.8	1850.7	105.8	457.6	27.2
Predicted Duration (sec)	585	195	108	137	645	753	1903	83	460	13
Error	3%	3%	20%	11%	-5%	0%	-3%	22%	-1%	52%

5 DISCRETE EVENT SIMULATION INPUT MODELING

Generally, experimental data can be used in three ways in a simulation: selecting one of the observed data points every time, randomly using a sample from collected model, and fitting a theoretical data to the model (Law et al. 1991). In the context of this work where data from experiment is used as input to run a simulation mode, previous research has shown that the first two methods are inappropriate as they cannot fully capture the variability and range of the dataset (Akhavian 2015). Stroboscope can model Scaled Beta, Erlang, exponential, Gamma, Normal, PERT Beta, triangular, and uniform distributions (Martinez et al. 1994). In this research, these distributions are tested for goodness of fit in describing extracted activity durations using three tests: Chi-Square, Kolmogorov-Smirnov (K-S), and Anderson-Darling (A-D) (Banks 1998). Table 3 shows the results of the goodness-of-fit tests, their rankings, and the numerical total of the ranks for activity 'Unload'. Since the Normal distribution resulted in the best total ranking, it was ultimately selected to describe the duration of activity 'Unload' in the simulation model. Similar analyses were conducted for all other activities.

Table 3: Ranking of the best fitted probability for activity 'Unload'.

Distribution	**K-S**		**A-D**		**Chi-Squared**		**Total**
	Statistic	**Rank**	**Statistic**	**Rank**	**Statistic**	**Rank**	
Beta	0.28296	2	11.422	8	N/A		10
Erlang	0.37122	6	2.6008	3	0.31304	3	12
Exponential	0.55156	8	6.1967	5	1.7434	6	19
Gamma	0.32795	4	2.1805	2	0.20342	1	7
Normal	0.30586	3	1.6871	1	0.219	2	**6**
PERT	0.27188	1	9.3159	7	0.38599	4	12
Triangular	0.42002	7	6.964	6	1.2962	5	18
Uniform	0.34273	5	5.6715	4	N/A		9

Table 4 shows selected distribution and its parameters for each activity. In addition, classification results were used to determine the probability of a box accepted or rejected. For instance, it was found that 29 instances of activity 'Load' followed activity 'Pull' which implies that in total, 29 boxes were moved in the system. Similarly, 20 instances of activity 'Unload' followed activity 'Push' which means that 20 boxes were accepted by the Inspector. Therefore, it was inferred that the ratio of accept/reject must be 20:9.

Table 4: Selected distributions and their parameters for activity durations.

Agent	Activity	Distribution	Parameters
Worker	Load	Gamma	a = 22.57 b = 0.28418
	Unload	Scaled Beta	Low = -29.258 High = 21.09 $\alpha 1$ = 196.84 $\alpha 2$ = 92.451
	Lower	Normal	μ = 1.3086 σ = 6.4737
	Push to Inspect	Gamma	a = 120.05 b = 0.08776
	Push to Unload	Uniform	Low = 11.709 High = 19.291
	Pull after Reject	Normal	μ = 3.7786 σ = 12.5
	Pull after Unload	Normal	μ = 6.3539 σ = 28.091
Inspector	Lift	Normal	μ = 0.91676 σ = 3.0741
	Inspect	Normal	μ = 4.4341 σ = 14.375
	Reject	Uniform	Low = 1.6515 High = 3.5487

6 SIMULATION MODEL IMPLEMENTATION

In DES, activities are modelled as interdependent discrete events (Akhavian et al. 2011). Stroboscope is an object-oriented DES authoring language (Martinez et al. 1994), and has been used in various applications such as earthmoving (Marzouk and Moselhi 2003), and planning and management of bridge construction (Zaeri and Rotimi 2014). The activity cycle diagram (ACD) for the warehouse operation experiment is shown in Figure 3. General descriptions of network elements can be found in (Martinez et al. 1994). In the ACD of Figure 3, boxes start in 'BoxToMove' and arrive in either 'BoxDelivered' or 'BoxRejected'. This model moves three types of resources (boxes, workers, and inspectors) on nodes and links. A decision node is referred to as a 'Fork'. Fork 'InspectionOutcome' in Figure 3 and its link strengths (used to decide where to send a box) are defined as follows,

```
FORK INSPECTIONOUTCOME BOX; /Defining the fork
STRENGTH B9 20; /Number of boxes accepted
STRENGTH B7 9; /Number of boxes rejected
```

To better mimic the real world, a new resource called 'Space' is also introduced in two places to limit the number of simultaneous instances of 'Load' and 'Inspect' activities. Also, given that activities 'Inspect' and 'Remove' are modelled as two separate activities, it must be ensured that when a box is rejected, it is removed by the same inspector. This is done by attaching the inspector and box using an Assembler node (node 'A' in Figure 3) and creating a new resource called 'InspectorwithBox'. The inspector and box are later disassociated using a Disassembler (node 'D' in Figure 3). These two new nodes are defined as follows,

```
ASSEMBLER ASSEMBLERBEFOREINSPECT INSPECTORWITHBOX;
DISASSEMBLER DISASSEMBLERBEFORELOWER INSPECTORWITHBOX;
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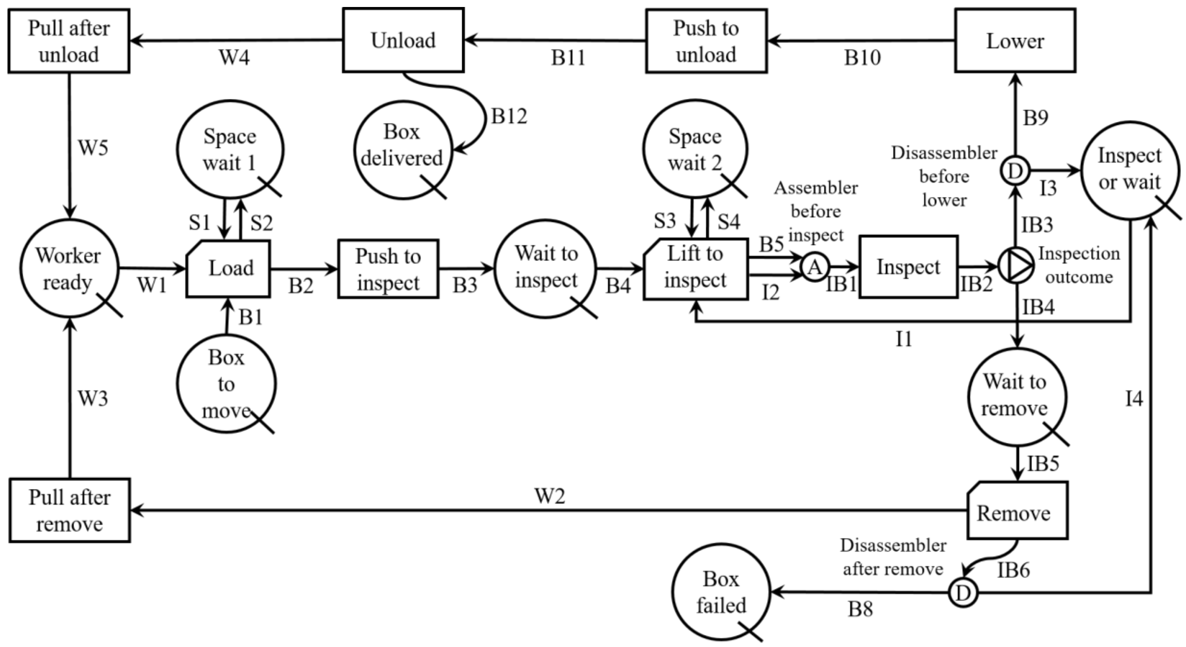

Figure 3: ACD diagram for the generated DES model.

The robustness of the simulation model and its scalability was validated using three simulations. In Simulation 1 the model was run 30 times with 1 worker and 1 inspector moving 30 to 900 boxes. Results in terms of ratio of expected (from real system) and obtained (from simulation) total time, inspector's idle time, and worker's idle time are shown in Figure 4. This Figure shows that the obtained time is within 10% of the experimental results for all three parameters thus validating the scalability of the model.

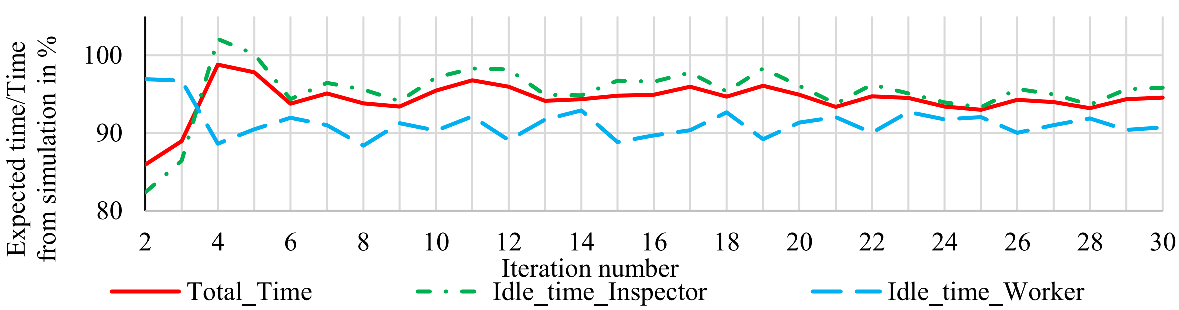

Figure 4: Ratio of expected and simulation times for Simulation 1.

In Simulation 2, the model was run with 30 boxes for 1,000 iterations. Results in terms of total time of the operation and idle time of the inspector are shown in Figure 5. This Figure shows that on average, simulation results are 6% lower than experimental results. This can be attributed to the seamless transition between simulated activities unlike in the real system where transitions take time. Furthermore, the activity recognition algorithm removes FDs from the data, thus contributing to the slight difference by weeding out the extreme values.

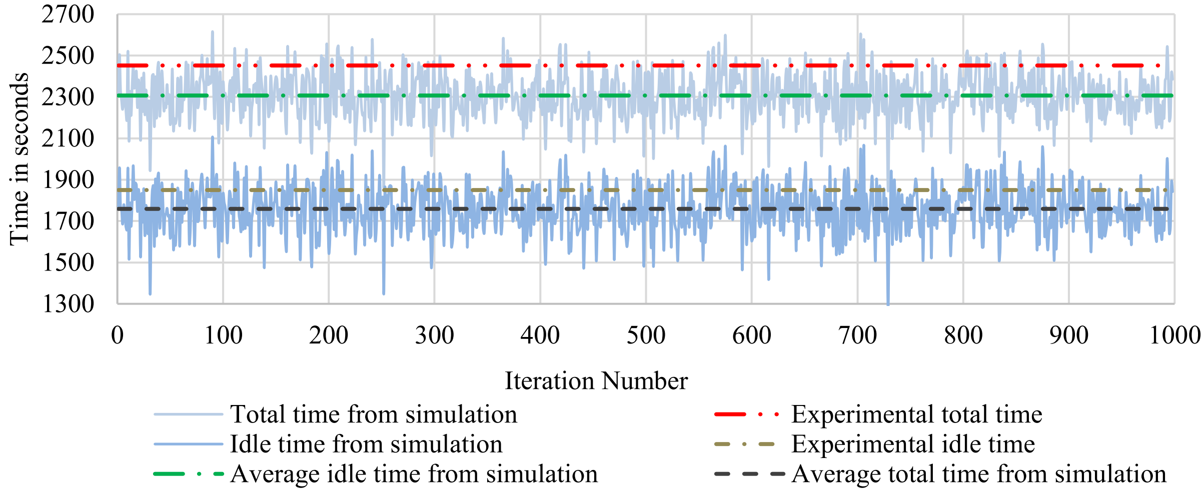

Figure 5: Simulation robustness in estimating total time and inspector's idle time.

Finally, simulation 3 was used to examine activity durations. In particular, 1,000 boxes were moved and average activity durations were collected. Comparison ratios between real world and simulation results are shown in the radar chart of Figure 6. As seen in this Figure, while the ratio of the durations from simulation model and durations from HAR is the most accurate of the three ratios, which highlights the validity of the simulation model, the least accurate ratio is the ratio of durations from HAR and observed durations, suggesting deficiencies in the quality of collected sensor data. Also, the ratio of durations from the simulation model and the observed durations is on average 90%, which is a decent approximation of the real world by the developed simulation model.

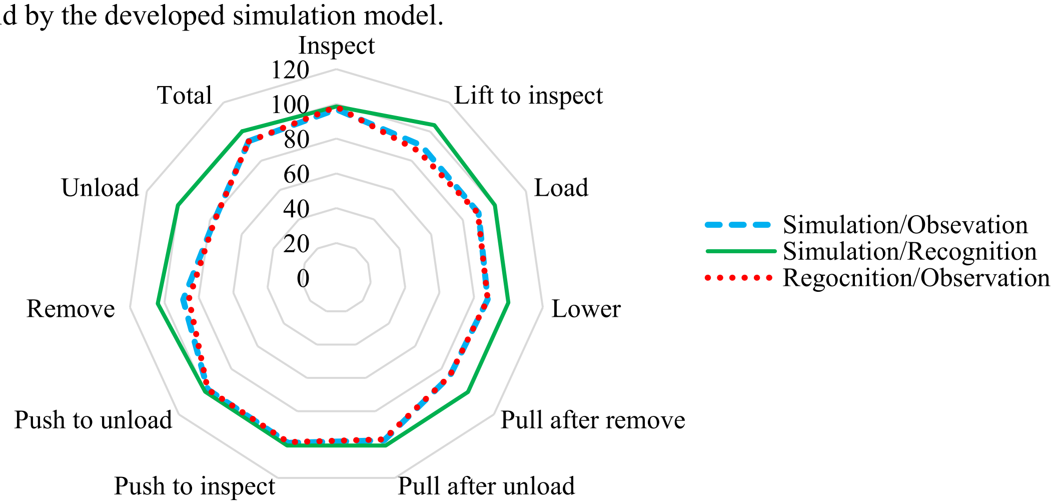

Figure 6: Simulation robustness in estimating activity durations.

7 WORKFLOW ANALYSIS

7.1 Process optimization

In the optimization stage, the cost to move each box with different worker-inspector combinations was examined. Workers and inspectors were assigned an hourly cost of \$15.34 and \$33.92, respectively (BLS 2015). The initial workflow simulation examined the trends in cost with variations in the number of workers and inspectors (Figure 7). Results show that unit cost for inspecting a box, in this particular case, is minimum with 25 workers and 6 inspectors (Figure 7).

Figure 7: Unit cost of inspecting a box for various worker-inspector combinations.

Evidentially, bottlenecks play an important role in project cost. In this experiment, with one inspector and more than four workers, an increase in the number of workers increases the cost, whereas with 10 inspectors the bottleneck is removed thus, cost decreases when the number of workers increases (Figure 7). As expected, worker's efficiency decreases with an increase in the number of workers, and increases with an increase in the number of inspectors (Figure 8a). Furthermore, inspector's efficiency rises to 100% (Figure 8b) whereas worker's efficiency remains below 80% (Figure 8a). In the experiment, workers wait idly during 'Inspect' and 'Reject' activities, hence creating the lower cap on efficiency. The effect of bottlenecks in this experiment can be also observed in that the number of workers required for inspector's efficiency to reach 100% increases as the number of inspectors increases (Figure 8b).

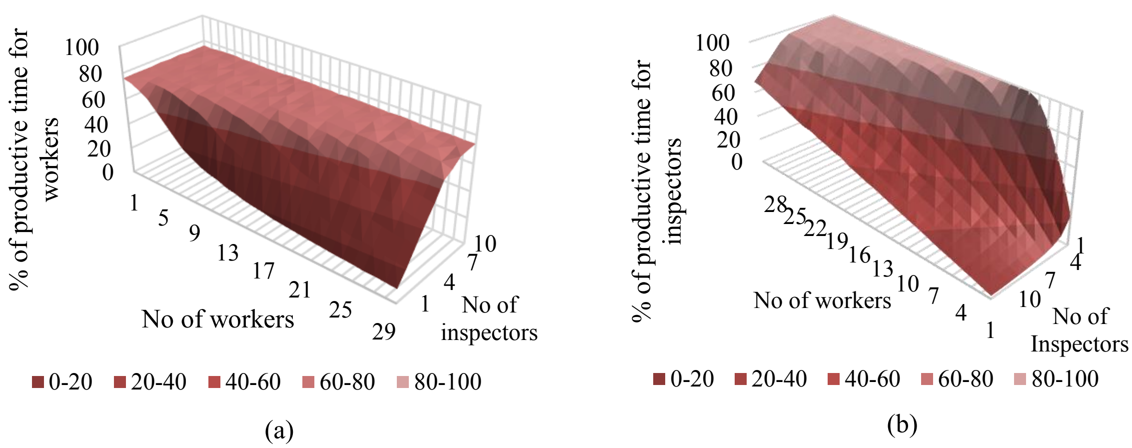

Figure 8: Productive time for different combinations of workers and inspectors.

7.2 Productivity and Cost Analyses

In the further analysis stage, various simulation model parameters were altered to examine the relationship between the productivity at minimum cost and cost at maximum productivity. This analysis is an illustration of the various possible applications of the parametric model built to analyze the data. In particular, 18,000 iterations were run by varying the input parameters as follows: number of workers from 1 to 30, number of inspectors from 1 to 10, inspector spaces from 1 to 3, worker spaces from 1 to 5, and number of boxes from 100, to 1,000, 10,000 and 100,000. For each simulation, total cost, total simulation time, inspector's idle time, and worker's active time were recorded.

With the goal of evaluating the effect of physical space as expressed by 'Worker's Space' and 'Inspector's Space', each combination of worker's space, inspector's space, and number of boxes was taken as a unique optimization problem and the numbers of workers and inspectors were taken as variables. For each of the 60 optimizations, the combination of number of workers and number of inspectors with the minimum cost and their productivity, and the combination of number of workers and number of inspectors with the maximum productivity and the cost at that combination were recorded. Finally, the difference between productivity at minimum cost and maximum productivity, as well as cost at maximum productivity and minimum cost were calculated in percentage. Figure 9 illustrates the relationship between the percentage difference in cost and percentage difference in productivity. One interesting observation that can be drawn is that for most of the combinations, the percentage increase in cost is significantly more than the percentage increase in productivity. This suggests that increasing productivity from the productivity at lowest cost can be very costly.

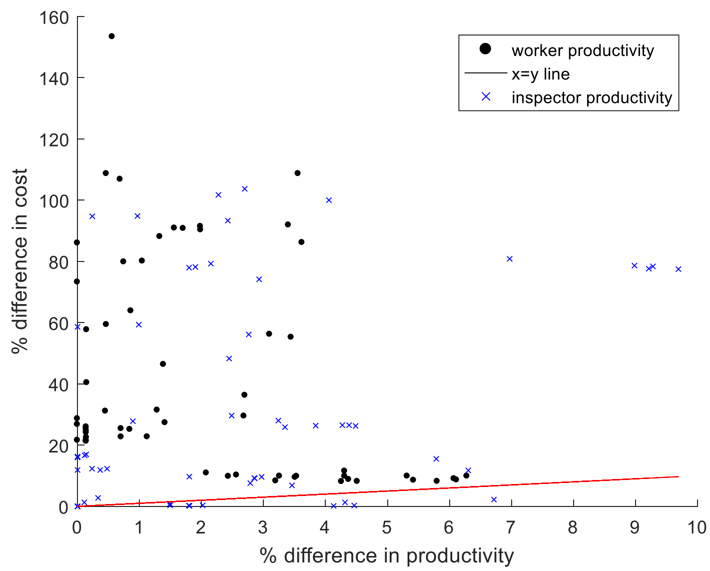

Figure 9: Difference between productivity and cost at maximum productivity and minimum cost.

8 DISCUSSION

In this research, first, wearable sensor data and machine learning were used for HAR. Seven out of 10 activities were recognized with >80% accuracy. For activities 'Push' and 'Pull' for worker, and 'Wait' and 'Inspect' for inspector, accuracies were even higher (>95%). Activity durations were extracted from classifier predictions. For 6 activities, extracted durations were within 5% of true values. For activities 'Pull' for worker, and 'Inspect' for inspector, extracted durations were within 1% of true values. From extracted durations, best statistical distributions were selected as inputs in a data-driven simulation model. Three versions of the simulation were run in multiple iterations to test robustness and scalability. Simulation results with uniformly distributed number of boxes from 30 to 900 showed that on average, output durations were within 10% of the experimental average. The second simulation with 30 boxes and 1000 iterations showed that on average, output durations were 6% lower than true values. For workflow optimization, space constraints and various crew combinations were used. Simulation results showed that in the presence of only one inspector (bottleneck), cost increased with an increase in the number of workers. But for other cases, cost decreased when the number of workers increased. Moreover, worker's efficiency decreased with an increase in the number of workers, but increased when the number of inspector increased. Results also showed that inspector's efficiency can reach 100%, but worker's efficiency is capped at below 80%.

Furthermore, simulation results showed that for various combinations of numbers of workers and number of inspectors, the percentage increase in cost is significantly more than the percentage increase in productivity.

It is worth mentioning that although incorporating positional data for example from the smartphone's built-in global positioning system (GPS) sensor could have added some (marginal) value to the data analysis, it would have as well taken away from the flexibility of conducting experiments in an indoor environment. As shown in Figure 2, even without the inclusion of positional data, almost all activities were predicted with very high accuracy. Also, the limited number of work cycles in the experiment presented in this paper resulted in a relatively small dataset, which in turn necessitated the use of more data collection nodes (i.e. smartphones) on each person to accommodate for the lack of distinctive features in collected data. In future experiments, increasing the number of cycles as well as capturing data from more sensors in each smartphone will help authors move toward using only one data collection node (e.g. smartphone) on each person. Finally, it should be noted that while some of the observations and conclusions made in this paper may be specific to the experiment conducted in this research, as well as the nature of data collected from the individuals who performed various activities, the designed methodology and overall approach to problems such as process optimization, and productivity and cost analyses using sensor data and machine learning is generalizable to other types of operations of arbitrary length and complexity.

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