Proceedings of the 2018 Winter Simulation Conference
M. Rabe, A.A. Juan, N. Mustafee, A. Skoogh, S. Jain, and B. Johansson, eds.

PRODUCTIVITY IMPROVEMENT IN OPERATING AUTONOMOUS PLANTS SUBJECT TO RANDOM BREAKDOWNS IN CONSTRUCTION

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ABSTRACT

Realizing continuous operations of autonomous plants subject to finite specialist crew resources for maintenance and repair is vital to achieving productivity and cost-effectiveness in construction operations. This paper presents a practical Monte Carlo simulation-based method to develop autonomous plants operations and maintenance programs. To balance the cost of plant production loss against the cost of hiring maintenance crews, we define a cost function which factors in production output value, resource utilization efficiency and direct cost in connection with both autonomous plants and maintenance crews. An illustration case of planning maintenance crew resources in operating autonomous crushing plants at a quarry site is used to shed light on required input data, simulation processing, and output analysis. The case also has increasing relevance to the construction industry in the near future in terms of planning the operation of a fleet of autonomous equipment in site operations.

1 INTRODUCTION

In construction, productivity is "a measure of the overall effectiveness of an operating system in utilizing labor, equipment and capital to convert labor efforts into useful output" (Hendrickson 2008). Compared with other industries (e.g., manufacturing, power, heavy chemical, and mining), the construction industry has made the highest amount of investment in machinery with an aim to deliver higher productivity and to save cost (Yoon et al. 2014). The high ownership cost of these massive construction machinery pressures construction companies to make the most use of them by operating at the highest efficiency practically possible in order to meet the tight project deadline; while at the same time maximizing the productivity and profit margin. Occasionally, the use of major construction equipment is planned to operate even for a whole construction season without stopping for a single moment (Vision 2017). The technological revolution has materialized the dream of turning heavy equipment into autonomous robots, at the same time presenting new challenges in planning the equipment maintenance program. Autonomous control systems on plants or equipment feature complex engineering system design and operate on a host of sensor technologies and intelligent algorithms for positioning (Hasan and Lu 2018), communication, and control of the mechanical systems (Radziwon et al. 2014).

Malfunctioning or breakdown on the autonomous control systems would cause interruption to equipment operations and give rise to prohibitively expensive costs in terms of production loss and equipment idling. Thus, such events present significant risks to disrupt the entire production or construction system despite the relatively small probability of occurrence considering each individual piece of equipment (Finch et al. 1986). This is also evidenced by recent news in the construction and mining industry: in implementing a fleet of autonomous trucks, major mining companies decide to keep a certain number of driver jobs as backup to operate non-autonomous trucks in order to maximize the full potential of new technology (Healing 2018).

How to provide system maintenance resources and plan backup production resources in a cost-effective manner such that the production interruption is mitigated presents an interesting problem to investigate. While the autonomous control system is being rebooted, repaired by a specialist maintenance crew, the equipment switches to a manual mode and continues operation by the maintenance crew without incurring any stoppage. Alternatively, a manually operated spare plant temporarily substitutes for the autonomous plant to keep the production system operating at its full capacity until the autonomous plant is up running again.

This paper presents a practical Monte Carlo simulation-based approach to address the above identified problem. The example of planning maintenance crew resources in operating autonomous crushing plants at a quarry site is adapted from Tang et al. (2004) as an illustration case. The case has increasing relevance to the construction industry in the near future in the particular context of planning maintenance crew resources in running a fleet of autonomous equipment in site operations. It is noteworthy that the original case has small-sized samples of input data and subjectively estimated information on breakdown probabilities and duration categories for maintaining the plant autonomous control system. With limited input data, simple discrete probability functions are fitted to inform random sampling in the simulation. Nonetheless, this case provides clear guidance on what data to collect and how to perform the complete analysis. As a matter of fact, for similar applications down the path, the required data will be automatically collected by using proper sensors. As such, more sophisticated statistical distributions can be fitted onto larger more realistic datasets in practical applications down the path.

2 LITERATURE REVIEW

Globalization, along with technological advances, has made reliability and productivity of a production system the key determinant factor for manufacturing companies to thrive in the competitive market (Muchiri and Pintelon 2008). Implementation of smart planning and supply chain management schemes with installation of computer integrated autonomous production lines improved the performance indicator of this industry (Tang 2006). As noted by Ashayeri et al. (1996), utilization of expensive, specialized computer controlled equipment potentially decreases the production cost but demands proper maintenance scheduling and special contingency planning for backup manual operation. Often, these maintenance crews or backup manual operation crews may require a high skill set to perform the job and can be very expensive (Finch and Gilbert 1886). Therefore, it is critical to optimize the crew size and plan the deployment schedule for such backup crews in order to maximize cost-effectiveness of the whole production system while delivering higher profit margins.

Construction operation is dynamic in nature which involves outdoor operating conditions and can be influenced by many variables (e.g., time, place, equipment, weather, construction method, etc.). As pointed out by Louis and Dunston (2017), the dynamic nature of the construction operations substantially increases the inherent uncertainty in adaptation of computer controlled autonomous solutions for construction operation in comparison with the manufacturing operation setting. With advances of the smart technology, the construction industry is also catching up with manufacturing. According to Aziz et al. (2013) adaptation of autonomous or semi-autonomous construction machinery and coping with the construction environment with smart planning solutions provide key foci for construction researchers at present and in the near future. Similar to manufacturing, the vision of continuous production has been realized in practice by many major earthworks and mining contractors (Vision 2017). Hasan and Lu (2017) presented the concept of a continuous operation plan for an autonomous backhoe excavator which operates on a large grading site. Momin et al. (2015) addressed different autonomous solutions for road construction. Neelamkavil (2009) gave a broad view of the essence of construction automation for prefabrication industry (particularly in housing) and made a fair comparison with other manufacturing industries.

Relevant literature corroborates the fact that the deployment of autonomous computer-controlled technologies in general gives rise to inevitable construction productivity improvement. Autonomous machinery generally feature complex system design and demands expert's hand to fix if any breakdown occurs (Buchanan and Bessant 1985). In the manufacturing setting, this type of situation can be handled by transferring the job order to another plant at a different location (Chopra and Sodhi 2004) but it is practically infeasible for construction. To keep the operation continuous while avoiding production interruption and productivity loss, the common practice in construction is to keep the option of manual operation as a backup. Therefore, crew resources for plant maintenance and manual operation backup needs meticulous planning in terms of utilization efficiency and crew size (Siu et al. 2014).

As noted by Siu et al. (2016) four categories of methodologies are generally applied in resource use optimization and scheduling research. These are (1) heuristic rules; (2) evolutionary algorithms; (3) simulation models; and (4) mathematical programming. The simulation-based resource use optimization approach is commonly recognized the best match for the problem being addressed. In particular, the Monte Carlo (MC) simulation approach is applied to model plant breakdown on a random basis in the case study, which follows the straightforward random event scheduling and random duration sampling strategy, resulting in the bar chart schedule representing specific breakdown periods on particular plants during a specified operation time frame (say 24 hours). To our best knowledge, no quantitative techniques other than Monte Carlos simulation provide the analytical solution to the key decision variable–which is the duration for a certain number of plants experiencing simultaneous breakdowns is determined by random sampling. To facilitate the decision process and structure the analysis of simulation output, the present research further defines cost functions on top of the simulation model by factoring production output value, resource utilization efficiency and direct cost in connection with both autonomous plants and maintenance crews. This allows for a better analytical approach to balance the cost of plant production loss against the cost of hiring maintenance crews and identify the optimum solution, thereby lending straightforward decision support.

3 CASE OVERVIEW

In this case, a large construction company owns and operates fifteen identical autonomous crushing plants in a quarry site to produce aggregates. In any working hour, the probability for a plant running under "auto mode" to breakdown along with the certain duration of breakdown is known from historical data. For demonstration purpose, the probabilities to experience the auto breakdown of different categories in any working hour are defined as a discrete distribution function for any crushing plant.

In this case, it is assumed that the autonomous control system breakdown will be repaired by itself after a certain period of running self-diagnosis software and system reboot software; at the meantime, if a standby crew is available, the plant switches to "manual mode" of operation; as such, production loss is avoided during the auto system down period. Otherwise, if the crew is not available, the plant stops production, incurring production loss. The plant will resume autonomous operation at the end of the breakdown period.

In contrast with the solution originally given in (Tang et al. 2004), the proposed methodology extends the simulation output analysis by defining a consolidated cost function called *Net Production Output, NPO* as in Eq. (1), which considers the value of plant production output and the cost of hiring maintenance crews, while simultaneously factoring in utilization efficiencies for those autonomous plants and crews employed.

$$NPO = PPU - MCC \tag{1}$$

Here, *PPU* = *Plant Production Output*;
MCC = *Maintenance crew cost*, can be calculated by using following Equations (2) and (3) respectively,

$$PPU = \sum_{1}^{N_p} PHR \times Hr_{EOP} \qquad (2)$$

$$MCC = Nc \times CHR \times Hr_{OP} \qquad (3)$$

Here, *Np = Number of plant*;
Nc = Number of crew hired;
PHR = Plant's hourly production output value without stoppage ($/h);
Hr_{EOP} = *Effective operation hours on each plant,* as per equation (4);
CHR = Crew hourly rate ($/h);
Hr_{OP} = *Total operation hour*.

$$Hr_{EOP} = Hr_{OP} - [Inturupted, Hr_{OP}] \qquad (4)$$

$$PHR = f\left(\sum c_i\right) ; \quad i = 1, 2, 3, \ldots\ldots, n \qquad (5)$$

Where, c_i is the itemized cost due to breakdown per unit product, which accounts all direct and indirect production costs.

Here, the *NPO* essentially factors in the plant utilization efficiency for each of all the plants (e.g., autonomous plant efficiency factor generally fall in the range above 90%); which is factored in the effective operation hours on each plant in (2), the higher this ratio (closer to 100%), the higher plant production output, hence, the higher *NPO*. On the other hand, the manual crew utilization efficiency (e.g., manual crew utilization efficiency factor generally is around 50%: half of the time crew engaged in operating plants; half of the time standby) is loosely reflected in the maintenance crew cost: if too many crews are hired, the crew utilization efficiency will be much lower, as a result, driving up the maintenance crew cost and reducing the *NPO* as per Eq. (1).

In short, *NPO* provides an effective performance indicator for both system productivity and resource use efficiency in the current case. In order to improve productivity and resource use efficiency the objective is to maximize *NPO*.

4 PROCESS SIMULATION

For the aforementioned case in Tang et al. (2004), the probabilities for the four categories of auto system breakdown add up to 20% (Table 1); the rest 80% of the time the plant runs on its autonomous mode without any problems. Anticipated crew hourly rate, *CHR* is $312.5/hr (overtime or night shift factors are considered in this average rate), and the hourly production output, *PHR* of a crushing plant is $10,000/hr.

Table 1: Crushing plant breakdown statistics.

Breakdown Category	Probability	Down Time
CAT I	0.08	0.5 hour
CAT II	0.06	1.0 hour
CAT III	0.04	1.5 hour
CAT IV	0.02	2.0 hour

4.1 Single Simulation Run

Considering the above input setting, a single simulation run to simulate plant breakdown events for 5 hour duration is illustrated in Figure 1. Table 2 summarizes the plant breakdown hours corresponding to the number of plants which would break down at the same time during the five hours time period, alongside the scaled up time duration in terms of the twenty four hours operation period.

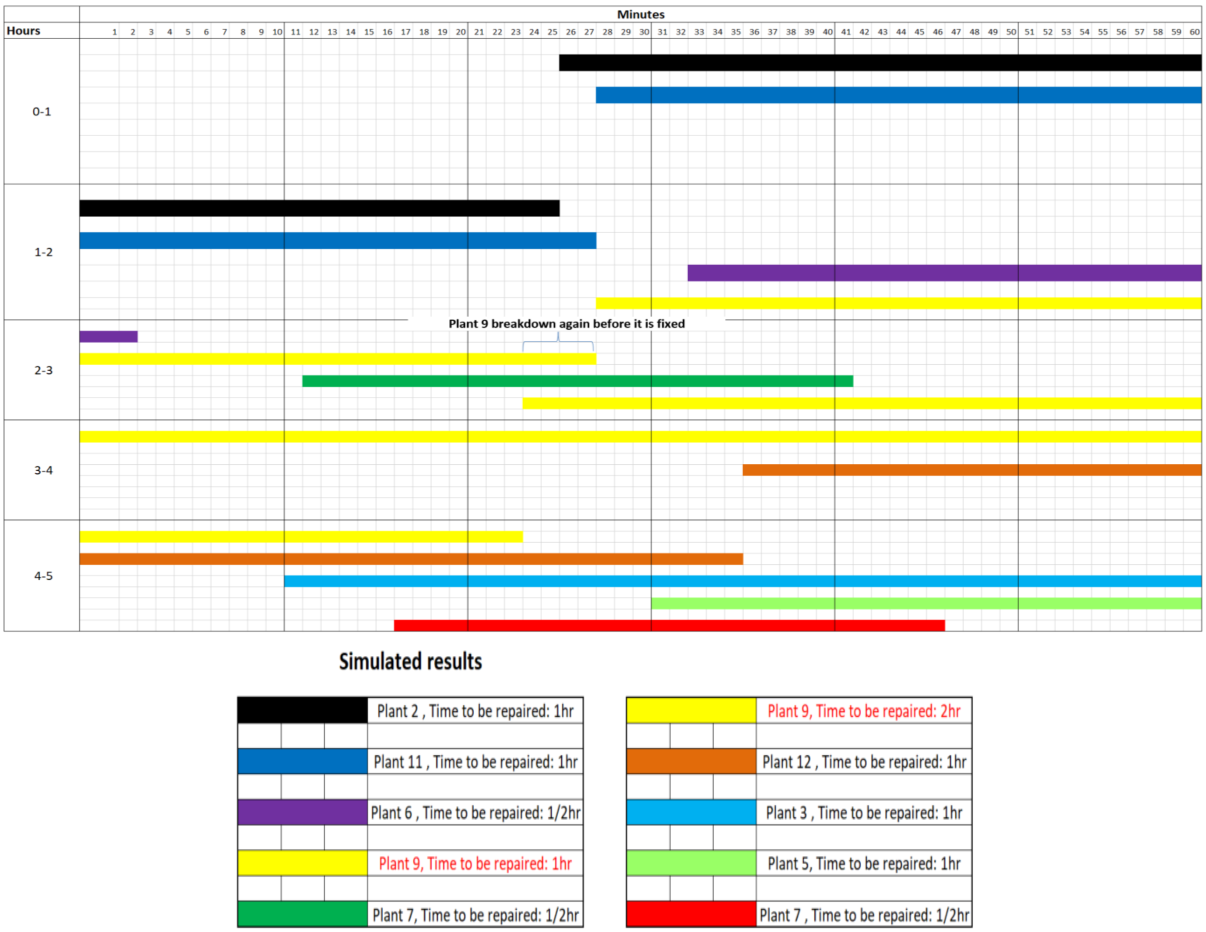

Figure 1: Plant breakdown simulation bar chart from one run over five hours.

Table 2: Solution demo based on one run Monte Carlo scaled up to twenty four hours of operations.

No. of plants broken down at the same time	**No. of minutes**	**Equivalent hours per day**
0	25	2.00
1	72	5.76
2	167	13.36
3	24	1.92
4	12	0.96
5	0	0.00
Total	300	24

Based on simulated down times, various scenarios for crew allocation are analyzed independently, namely, 5 crews, 4 crews, 3 crews, 2 crews, and 1 crew. For instance, if 4 crews are allocated, using Equations (1) to (4), following values can be determined,

From equation (2), $PPU = \sum_{1}^{N_p} PHR \times Hr_{EOP} = 15 \times 10{,}000 \times 24 = \$3{,}600{,}000$
From equation (3), $MCC = Nc \times CHR \times Hr_{OP} = 4 \times 312.5 \times 24 = \$30{,}000$

Thus, the net production output value, NPO is fixed as per Equation (1), which is $(PPU - MCC) = 3{,}570{,}000\$$. For this scenario, the crew use scheduling results in 44% crew utilization rate (working time percent) in keeping the 15 crushing plants running over 24 hours without any production loss time. If three crews are employed, using the same set of equations, the daily production, *PPU* can be found to be \$3,590,400 due to some plant production loss (\$9,600 for 0.96 hr). The crew utilization is updated at 57% and the total net output, *NPO* is at \$3,567,900. Compared against the "deploying 4 crews" scenario, the net output in "3 Crews" Scenario reduces marginally by \$2,100 (from \$3,570,000 with 4 crews to \$ 3,567,990 with 3 crews), while the crew utilization rate increases from 44% to 57%. Figure 2 shows the change of *NPO* with the different crew number, *Nc* which is conducive to identifying the maximum productivity of the plant operation. For this simulation run, it is evident in Figure 2 that the maximum value of *NPO* = \$3.570 million is obtained when four maintenance crews are assigned as backup.

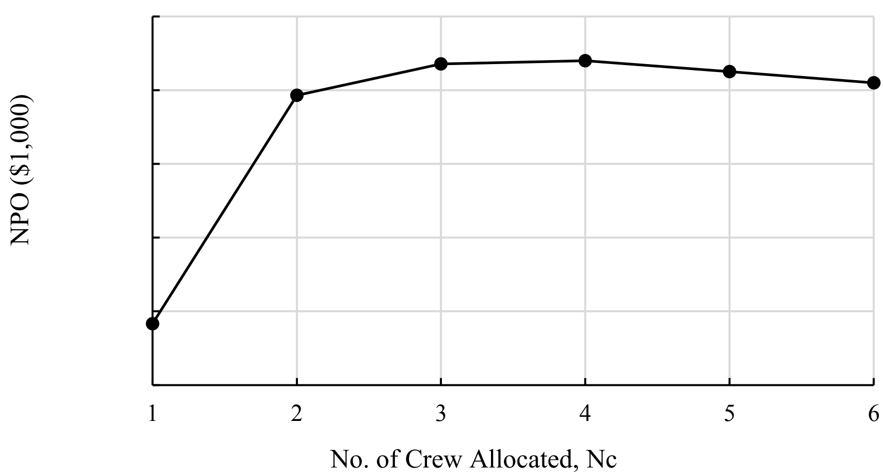

Figure 2: Change for *NPO* with different crew number for the first MC run.

4.2 Multiple Simulation Runs

The entire procedure for a single simulation run discussed above is repeated for thirty independent Monte Carlo duplications. The values of *NPO* with corresponding *Nc* for each simulation run are plotted together in the same Figure 3(a). The resulting *NPO* verses *Nc* plot show, instead of having a single point value of *NPO* for each number of allocated crews, the *NPO* is now a cluster of points, each point denoting the independent solution obtained from multiple simulation runs. The series of clusters is separately depicted in Figure 3(b) with a box plot for better illustration of the distribution of the data clusters.

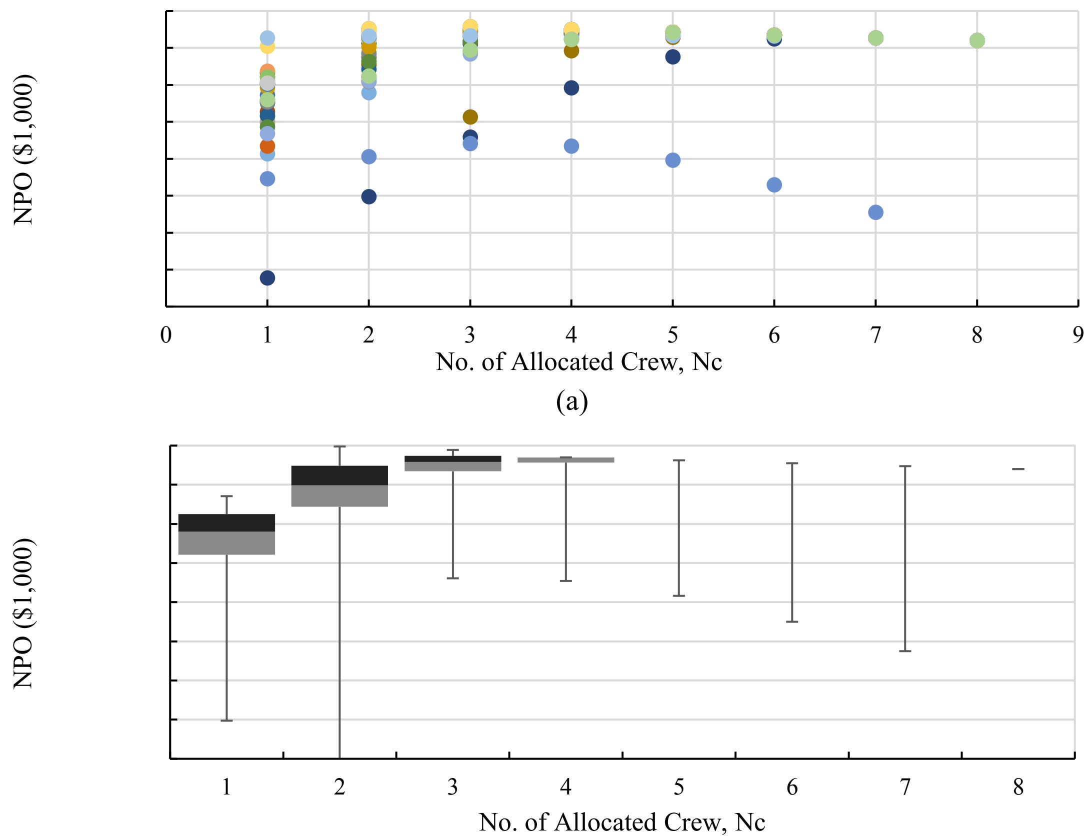

Figure 3: Change for *NPO* with different crew number for 30 independent MC run, (a) the cluster of *NPO* values for corresponding *Nc* value, (b) the box plot for each *NPO* data group.

In Figure 3, all the points cluster so closely given the number of crew is 7 or 8, as most of the simulated output NPO fall on the same spot. Note, the majority of simulation runs yields maximum NPO at 4 or 5 crews. Adding more crews beyond 5 results in no interruption in the plants' operation, while the maintenance crew cost increases linearly. Thus, the NPO remains the same. Besides, Table 3 summarizes the average (Avg.) and standard deviation (Std. dev.) for each data cluster resulting from multiple simulation runs.

Table 3: Simulation statistics for each group of NPO values for corresponding Nc value.

Nc	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Avg. NPO (Million $)	$3.363	$3.482	$3.536	$3.548	$3.548	$3.541	$3.532	$3.540
Std. dev. of NPO (Million $)	$0.122	$0.101	$0.077	$0.064	$0.065	$0.075	$0.088	$0.000
95% confidence interval of NPO [Low, High] (Million $)	[3.124, 3.602]	[3.285, 3.679]	[3.385, 3.685]	[3.423, 3.673]	[3.420, 3.675]	[3.393, 3.689]	[3.359, 3.703]	-

4.3 Output Analysis

To make the critical resource planning decision about how many crews should be deployed to operate the 15 autonomous crushing plants, the lower bound of the 95% confidence interval of *Net Production Output (NPO)* is plotted against different crew number (*Nc*) in Figure 4, which is based on statistical analysis of simulation output. From Figure 4 it is evident that the deployment of four backup manual crews (*Nc* = 4) yields the maximum *NPO* value. So, the optimum number of manual crews is identified as four, which has the highest likelihood to maximize *NPO* in the range of [3.423, 3.673] Million $.

Figure 4: Lower bound of the 95% confidence interval of Net Production Output, (NPO) values for different crew number (Nc).

4.3.1 Sensitivity Analysis

To check the sensitivity of the effect of the crew hourly rate (CHR) on the crew size (Nc), the simulation output is analyzed for different crew hourly rates (adjusted up or down by 20% and 50% respectively, implying the likely fluctuation of crew hourly rate in reality) and presented in the following Figure 5. It is observable that there is no significant change in crew number which outputs maximum NPO value due to the change of CHR in the range of [-50%, +50%]. For this example case, the crew number which yields maximum NPO remains four (Nc = 4).

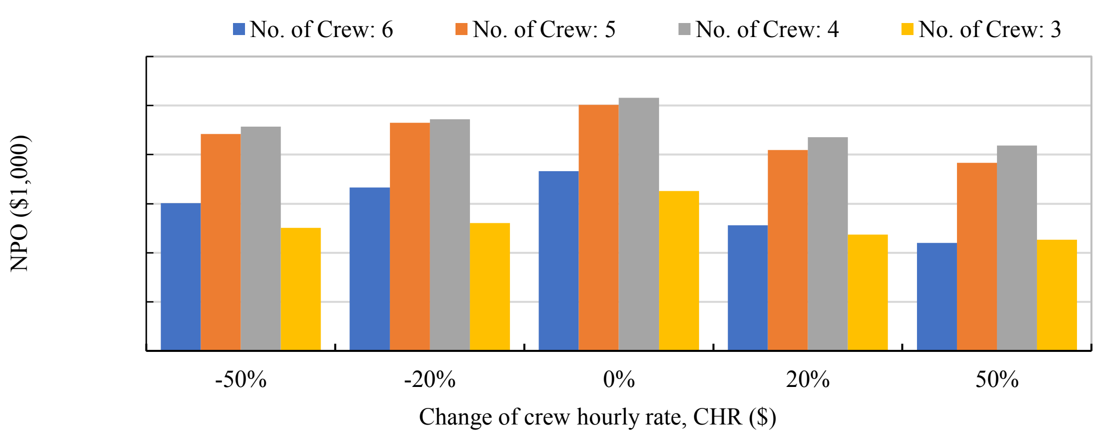

Figure 5: Change of NPO value for the different crew hourly rate.

4.3.2 Crew Utilization

Crew utilization rate is defined as the ratio between the crew working hours and total crew deployed hours. For the first MC run for this case study (discussed in Section 4.1), the crew utilization status given four and three manual operation crews are deployed is illustrated in Figure 6(a) and 6(b), respectively. Hence, when four crews are allocated, simulation results in 44% crew utilization rate (working time percent) in keeping the 15 plants running over 24 hours without any production loss time. Thus, plants production efficiency (net output /net capacity) is 100 %. If three crews are employed, using the same set of equations, crew utilization increases to 57%; while at the same time, the plants' efficiency slightly decreases to 99.4%.

4 Crew Allocation

No. od plant broken down	0	1	2	3	4
Duration (hrs)	2	5.76	13.36	1.92	0.96
Crew idled	4	3	2	1	0
Crew used	0	1	2	3	4
Crew allocated, *Nc*	4	4	4	4	4
PPU (daily)	$3,600,000				
NPO (daily)	$3,570,000				
Utilization Rate	43.83%				

(a)

3 Crew Allocation

No. od plant broken down	0	1	2	3	4
Duration (hrs)	2	5.76	13.36	1.92	0.96
Crew idled	3	2	1	0	0
Crew used	0	1	2	3	3
Crew allocated, *Nc*	3	3	3	3	3
PPU (daily)	$3,590,400				
NPO (daily)	$3,567,900				
Utilization Rate	57.11%				

(b)

Figure 6: Crew utilization scenario analyses for (a) four backup manual crews are allocated, (b) three crews are allocated.

For multiple simulation runs, crew utilization rate for different numbers of crew combinations are calculated based on simulation outputs, and statistics of the results are summarized in Table 4. Here, if 4 crews are deployed, the mean crew utilization rate is 45.02% which falls in the work percentage range of 40% to 65% benchmarking field labor activity in construction (Dozzi and AbouRizk 1993; Jergeas 2009; RSMOnline 2014). Note 45% work percentage is deemed practical in reality, as workers are not robots or machines; they are human beings working in a harsh environment. In contrast, the plant utilization rate is around 100%.

Table 4: Simulation statistics for crew utilization rate with corresponding Nc value.

Nc	**1**	**2**	**3**	**4**	**5**	**6**
Crew Utilization Rate, CUR	85.65%	72.79%	57.10%	45.02%	36.33%	30.18%
Std. dev. of CUR	7.30%	9.66%	9.88%	9.29%	8.80%	7.27%

5 RELEVANT APPLICATION PROBLEMS

Two separate case problems from the construction engineering domain are presented in this section to demonstrate the relevance of the proposed methodology to determine the manual backup crew deployment in support of utilizing autonomous technology in the construction field. The first case is termed as "autonomous truck breakdown problem" and the second one is about "automatic tunnel boring machine (TBM) guidance mechanism breakdown problem", explained as follows.

Autonomous Truck breakdown problem: In recent years autonomous dump trucks for mining or large-scale rough grading in construction can be found in the field as game-changing technology in the construction industry (Healing 2018). Autonomous trucks are capable of running without the driver. However, the automation control system on board may occasionally break down (random event), which needs to be diagnosed and repaired via wireless communication networks for a certain time of period. At the end of repair, the control software needs to be rebooted. In the meantime, a human driver can take control of the truck so to keep the operation running uninterruptedly.

Autonomous TBM guidance system breakdown problem: Another example is deployment of the automatic TBM guidance system in tunnel construction. Automatic survey robot substitutes for the manual alignment survey system which depends on the field service of the expert survey crew and demands temporary shutdown of TBM operation due to quality assurance requirements and confined work space in the tunnel (Shen et al. 2011). However, occasionally, this automatic survey control system can fail and needs significant time for repair and recalibration due to system malfunctioning or unanticipated disturbance to the system position. In order to keep the TBM operation running, a manual survey crew is called in as backup to guide TBM in the underground space along the as-designed tunnel alignment.

In both cases, backup crews are necessary to avoid productivity loss during the autonomous system downtime. The attributes given in Table 5 align these two construction engineering problems with the presented case of autonomous crushing plants.

Table 5: Relevant attributes for the construction engineering examples.

Features	**Crushing Plant**	**Autonomous hauling Truck**	**Autonomous TBM guidance system**
Autonomous Control System	Autonomous aggregate crushing plant	Autonomous (driverless) Truck	Autonomous survey robot for TBM guidance in tunneling
Breakdown Entity (Random)	Crushing plant (operation running mechanism) breakdown	Truck control system breakdown	Guidance system mechanism malfunction or calibration requirement
Breakdown Category	Discrete probabilities based on limited historical data of downtime.	Can be defined by analyzing automatically collected sensor data of downtime.	Can be defined by analyzing automatically collected sensor data of downtime.
Backup Crew	Plant operator	Truck driver	Tunnel surveyor

6 CONCLUSION

On top of a Monte Carlo simulation model for planning maintenance crew resources in operating autonomous crushing plants at a quarry, the present research defines cost functions by factoring the production output value, resource utilization efficiencies and direct costs in connection with both autonomous plants and maintenance crews. This enables more effective analyses on the simulation output and allows for a better, structured way to balance the cost of plant production loss against the cost of hiring maintenance crews, thereby facilitating the identification of the optimum solution and lending straightforward decision support. In particular, the cost function called *Net Production Output* value is found to be an effective performance indicator to facilitate the decision process based on interpreting simulation outputs. The application of the proposed simulation analysis methodology can be generalized from autonomous crushing plants in the present case study to a wide range of autonomous equipment, so as to nicely integrate productivity analysis, resource use efficiency, cost estimating, reliability analysis, and risk analysis in addressing such complex systems involving the interaction of autonomous systems and humans. Beyond the presented aggregate crushing plant case, relevant applications such as "autonomous truck breakdown problem" and "automatic tunnel boring machine (TBM) guidance mechanism breakdown problem" can be addressed by following the presented simulation methodology. In the near future, autonomous plants and equipment will not replace human beings entirely; instead, they will complement human beings to maximize the productivity gain as a result of technology advances. This is evidenced by recent news in the construction and mining industry: major mining companies implement a fleet of autonomous trucks, while still keeping a certain number of driver jobs as backup to operate non-autonomous trucks in order to maximize the full potential of new technology.

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