Aksakka, F., Yu, H., Hamzeh, F., & Al-Hussein, M. (2023). Factors influencing cycle times in offsite construction. *Proceedings of the 31st Annual Conference of the International Group for Lean Construction (IGLC31),* 723–734. doi.org/10.24928/2023/0123

FACTORS INFLUENCING CYCLE TIMES IN OFFSITE CONSTRUCTION

Fatima Alsakka[1], Haitao Yu[2], Farook Hamzeh[3], and Mohamed Al-Hussein[4]

ABSTRACT

In offsite construction, various factors contribute to variability in cycle times at workstations in production facilities, leading to imbalanced production lines. Understanding these factors is vital for implementing Heijunka, a fundamental lean principle that consists of levelling out the work schedule. This study presents a qualitative approach for identifying and understanding factors that influence variable cycle times at the workstation level. The application of the approach is demonstrated in reference to a semi-automated framing workstation in a panelised construction facility. A list of 36 potential influencing factors categorised into eight classes is first compiled based on observation of the process, a cross-functional diagram, and a review of relevant studies, and then discussed based on feedback solicited from personnel at the case framing station through a semi-structured interview. The approach, its application, and the results demonstrate the effect of expending effort on the identification and understanding of cycle time-influencing factors in improving the accuracy of cycle time analysis, thereby facilitating the implementation of Heijunka.

KEYWORDS

Offsite construction, lean construction, cycle time, influencing factors, Heijunka.

INTRODUCTION

MOTIVATION: THE HARE APPROACH

The offsite construction industry, also known as the construction manufacturing industry, is rooted in the broad shift of construction practice from traditional in-situ methods to manufacturing methods. One may intuit that moving towards manufacturing methods will inevitably pave the way for comprehensive and streamlined implementation of lean philosophy in construction. There is a degree of truth to this, as many offsite construction companies have sought to leverage the benefits of lean principles such as standardisation, waste reduction, continuous flow, production line balancing and others with the notable case of a panelised construction enterprise in Edmonton, Canada, applying these principles described in a recent study (Alsakka et al., 2022). Several studies have evaluated the benefits of implementing lean principles in offsite construction, including waste minimisation and workload and workforce density balancing in modular construction (Moghadam & Al-Hussein, 2013; Zhang, 2017), and batch and inventory size reduction in precast construction (El Sakka et al., 2016), to name a

[1] PhD candidate, Department of Civil and Environmental Engineering, University of Alberta, Edmonton, Alberta, Canada, falsakka@ualberta.ca, orcid.org/0000-0003-1777-1875

[2] Research and Development, Landmark Group of Companies Inc., Edmonton, Alberta, Canada, haitaoy@landmarkgroup.ca, https://orcid.org/0000-0002-7798-4867

[3] Associate Professor, Department of Civil and Environmental Engineering, University of Alberta, Edmonton, Alberta, Canada, hamzeh@ualberta.ca, orcid.org/0000-0002-3986-9534

[4] Professor, Department of Civil and Environmental Engineering, University of Alberta, Edmonton, Alberta, Canada, malhussein@ualberta.ca, orcid.org/0000-0002-1774-9718

few. In reality, however, the variable nature and other unique characteristics of construction make the implementation of lean manufacturing practices such as *Heijunka* (i.e., levelling out the work schedule (Liker, 2004)) inherently challenging . As argued by Ohno (1988) decades ago and reiterated by Liker (2004), "*the slower but consistent tortoise causes less waste and is much more desirable than the speedy hare that races ahead and then stops occasionally to doze. The Toyota Production System can be realized only when all the workers become tortoises*." The point here is not to advocate for slow production, but rather for steady production that reduces the likelihood of over- and under-utilisation of resources. The variability inherent in construction projects, however, forces workers and machines in offsite construction factories to follow the so-called "hare" approach. Let us consider, for example, a production line for fabricating wood house walls with one workstation dedicated to framing wall panels and another workstation dedicated to installing sheathing. Since walls are of different types, dimensions, and designs, the time it takes to frame a wall panel or install sheathing, if any, will vary depending on the wall type/design. As a result, if, for a given batch of panels, wall framing takes less time than sheathing installation, the workers at the sheathing workstation will be pressured to speed up their work to keep pace with the framers and keep the production line moving. If this batch is followed by a batch of interior walls for which no sheathing is installed, then the workers at the sheathing workstation will be under-utilised while the framers will be pressured to speed up their work to avoid starving the downstream workstations. In other words, the workers are pressured to function as "hares". Operators in offsite construction do endeavor to reallocate tasks among workstations in order to mitigate this effect, as described in Alsakka et al. (2022), but effective levelling of a production line requires detailed knowledge of the variable cycle times at workstations that is not readily available in current practice.

THE NEED FOR INFLUENCING FACTORS

Given this, researchers have employed machine-learning models trained to consider relevant influencing factors (or prediction variables) in order to estimate process time-related variables. For instance, Shafai (2012)—who argued that average task times should not be used to estimate the durations of highly variable tasks performed for manufacturing wall panels of different designs since the manufacturing time is contingent upon the unique design properties of each panel—built linear regression models for estimating the duration of each task (e.g., spray form insulation) as a function of the given panel's design properties relevant to the task at hand (e.g., number of studs, cut zone area, etc.). In another study, Benjaoran et al. (2004) used multivariable linear regression and neural networks to estimate the duration of production processes in a precast factory as a function of twenty influencing factors such as material weight and concrete strength. However, few studies are available in the literature that have followed this line of thinking for estimating process times or cycle times at the workstation level in offsite construction, although there are studies that have followed this paradigm for estimating other related variables, such as a study estimating man-hour requirements for structural steel fabrication jobs using linear regression (Hu et al., 2015), and another estimating the productivity of steel fitting activities in steel fabrication using artificial neural networks and simulation (Song & AbouRizk, 2008). Moreover, despite the critical role prediction variables play in determining the performance of machine-learning models, the identified studies either have not taken a systematic approach or have not thoroughly discussed the approach followed for identifying the factors that may have an effect on the time variables under study (i.e., task time, cycle time, man-hours, and productivity). The value of expending effort on such an approach is not only that it allows for the relevant influencing factors to be identified; it also helps modellers to gain knowledge about the process under study, in turn allowing them to follow a prescriptive approach for selecting and representing predictor variables (Kuhn & Johnson, 2019). In this manner, they can perform experience-driven modelling alongside empiricallydriven modelling, thereby reducing the risk of overfitting to erroneous data patterns or of generating models that cannot be rationally interpreted, compared to an approach that relies solely on empirical data (Kuhn & Johnson, 2019).

STUDY OBJECTIVE AND CONTRIBUTIONS

In this context, there is a need for a structured approach for identifying factors that could influence cycle times in offsite construction. This study thus presents a qualitative approach for identifying factors that influence cycle times at the workstation level in offsite construction factories. The identification of these factors, it should be noted, is an important preliminary step when deploying machine-learning techniques to develop cycle time prediction models as part of the lean practice of production line levelling. The approach is demonstrated through its application to a semi-automated, wood-wall framing workstation in a panelised manufacturing factory in Edmonton, Canada. The study contributions are as follows: (1) shedding light on the significance of analysing cycle times at the workstation level in offsite construction factories; (2) presenting the implementation of a generic approach as a way of encouraging researchers and practitioners to expend effort on identifying the factors influencing cycle time, which are significant for the performance and interpretability of machine-learning models developed to predict cycle times or related process time variables for the purpose of optimising production lines and production schedules (in order to ensure more balanced and efficient production); and (3) providing a preliminary list of factors that could influence cycle times at semi-automated wood framing workstations in offsite construction—a list that could serve as a starting point for researchers or practitioners studying other types of framing workstations.

APPROACH AND METHODS

The study followed a three-stage qualitative approach that leverages the benefits of process mapping and semi-structured interviews to identify the factors exerting an influence on cycle times at a wood framing station. The approach is presented in a generic manner in this section, while the next section describes its application to the case framing workstation.

STAGE I: UNDERSTAND THE PROCESS

An adequate understanding of the tasks involved in a process, the resources allocated to it, the manner in which the tasks are carried out, the process inputs, and of the process outputs enables rapid identification of a number of factors influencing cycle time. Process mapping of the current state, in turn, is an effective means of gaining a thorough understanding of a given process. Process mapping generates an abstraction of the process, allowing for it to be better understood and demonstrated and its performance assessed (Giachetti, 2011). The steps followed in building a process map are described in detail in a previous study by Alsakka et al. (2022). Validating the accuracy of the process map with input from the workers actually assigned to the workstation under study is crucial. The case application described in the present study demonstrates the significance of this validation task. The framing machine is equipped with a cutting saw that is used to cut through the top- and bottom-plates of the panels. Throughout the period of observation that formed the basis of the process mapping, the operator at the framing workstation was manually operating the cutting saw for every wall panel. As a result, moving the cutting saw was recorded as a step in the framing process. However, consultations with the operator revealed that in fact the framing machine was in disrepair, and hence, the operator was manually performing a step that would normally be performed automatically by the machine. In other words, what seemed to the analyst to be a normal part of the process (based on observation alone) was in fact the result of equipment breakdown (i.e., a factor affecting cycle time at the workstation). This example underscores the importance of validating the process map based on consultation with workers on the production line as a crucial step in identifying the factors influencing cycle time.

STAGE II: COMPILE A LIST OF POTENTIAL FACTORS

Based on the results of the first stage, the analyst may identify a variety of factors that influence cycle time at the workstation with regards to various elements involved in the process. The analyst may start by specifying high-level classes that could encompass the different types of factors to be identified, since doing so helps to structure and, hence, facilitate the process analysis task. In this respect, a set of eight major classes is proposed in the presented approach—“product”, “worker”, “machine”, “material”, “workstation setup”, “production line”, “factory operations”, and “external factors”—these classes having been preliminarily selected based on the authors’ understanding gained during the first stage, then confirmed based on a review of the relevant literature (refer to the Case Application section). In relation to each of these classes, the analyst may identify factors that influence cycle time at the workstation. (Examples of factors that belong to different classes are described in the case application section of this paper.) In addition to the process map, a review of previous research that analyses cycle times, productivity, or related aspects of the process under study, or of similar processes in offsite construction factories, could help to identify additional factors and, possibly, additional classes (over and above the eight classes proposed). At that juncture, the analyst would have a profound knowledge of the process under study and would be well positioned to extract relevant factors from the literature. It is advisable to extract all factors that could potentially have an impact on cycle time at this stage as doing so can further bolster the understanding of the process, even if some of the factors are ultimately excluded at a later stage. The outcome of this stage is a group of classes comprising factors that may impact cycle time at the workstation under study.

STAGE III: SOLICIT WORKERS’ INPUT ON THE FACTORS

As the cutting saw example described above demonstrates, the input of workers regarding cycle time-influencing factors is critical, since they are the most knowledgeable about the process. The workers’ input may help the analyst to better understand certain factors, highlight significant factors, determine which factors are less important, identify additional factors, or identify relationships between different factors. Hence, upon compiling a preliminary list of factors in the second stage, semi-structured interviews can be conducted to solicit workers’ input on the factors in the list. Semi-structured interviews, it should be noted, involve a mixture of close-ended and open-ended questions that are often followed with “why” or “how” questions (Adams, 2015). Semi-structured interviews are valuable when the interviewer (i.e., the analyst, in the context of this study) is interested in the independent thoughts of the interviewee (i.e., the worker) or when there are unknown but potential issues and the interviewer needs to pinpoint beneficial leads and pursue them (Adams, 2015). For each of the identified factors, the analyst may start by asking the worker if the factor affects or does not affect cycle time (i.e., a Yes/No question) and then asking follow-up questions such as “why it affects (or does not affect) cycle time”, “how it affects cycle time (i.e., positively/negatively)”, and “to what extent it affects cycle time (i.e., significance)”. In the case application presented in this study, this approach was found to trigger valuable discussions that yielded useful insights.

Given that a fixed and limited number of workers are typically assigned to each workstation in offsite construction factories, it is possible that some workstations will only have a single worker. This means that there may be just a single worker who is deeply knowledgeable about the current state of the process under study in some cases. However, this would not be critical, as the factors would have been previously identified based on a detailed analysis of the process and previous research work and will be further analysed during the machine-learning process in which the factors will be used. In other words, there are multiple input sources for the factors.

CASE APPLICATION

This section presents the implementation of the described approach on a semi-automated wood-wall framing workstation located in a panelised construction factory. In a recent case study on this workstation, cycle times were found to vary significantly, ranging from approximately 1 minute to about 48.5 minutes (Alsakka et al., 2023). This wide range of cycle times underscores the importance of determining the factors that influence cycle times at such workstations.

STAGE I: UNDERSTAND THE PROCESS

The case framing workstation has a semi-automated wood-wall framing machine that performs three operations: nailing, drilling, and cutting. An operator loads the machine with framing elements when prompted by the machine to do so, and the machine performs the required operations. An automated material feeding system moves studs from their inventory location to a location at the framing workstation from which the operator can directly pull them. The components are made ready half a shift or one shift before they are needed, and are placed on a rack located at the framing workstation in the same order in which they will be required by the framer. Moreover, the top and bottom plates of wall panels are stored on a rack located next to the workstation in such a manner that the operator can directly pull the plates to their loading locations on the framing machine. Figure 1 shows the locations of the different elements.

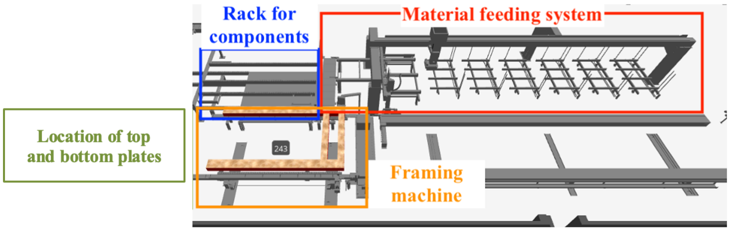

Figure 1: Virtual model of the framing workstation

Given that there are multiple resources (i.e., machine, operator, feeding system) interacting at the framing workstation to frame wall panels, cross-functional diagrams, also known as "swimlanes", were developed to aid understanding as to which tasks are performed by each resource. Cross-functional diagrams, it should be noted, are used to map the workflow of interrelated activities and resources that transform inputs into outputs, as well as to portray the relationships among the various resources performing actions (Damelio, 2011; Giachetti, 2011). A portion of the mapped diagram is displayed in Figure 2. The diagram was first mapped based on observation, and then verified and adjusted based on the operator's feedback.

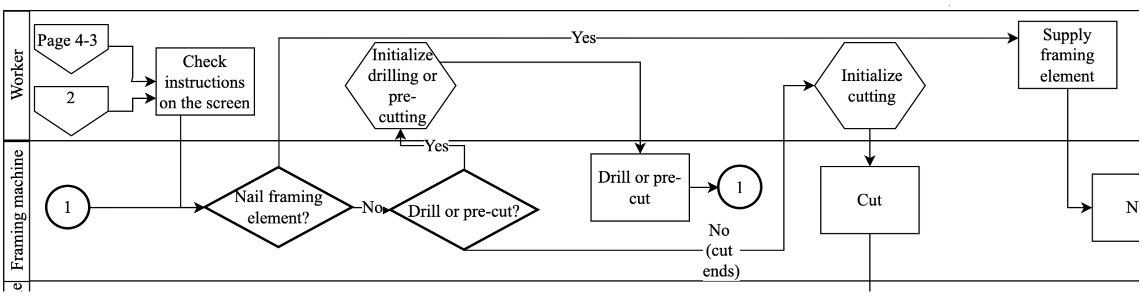

Figure 2: Portion of the framing workstation's cross-functional diagram

STAGE II: COMPILE A LIST OF POTENTIAL FACTORS

For each of the eight classes mentioned above, the factors understood to affect cycle times at the framing workstation were identified based on the authors' understanding gained during the first stage. This was followed by a review of the relevant literature to confirm the comprehensiveness of the classes identified. Because, as previously mentioned, only a limited number of directly related studies were identified, studies examining related metrics such as man-hour requirements and productivity were also reviewed. The factors identified in the relevant literature included, to name a few representative examples, (1) product-related (or design-related) factors such as [length, width, height, surface area,…] for the production of steel panels (Ayinla et al., 2019), [number of single studs, double studs, doors, windows, cut zones, drill holes, nails, screws,…] for the production of wood wall panels (Shafai, 2012), [number of fittings, cut-outs] for steel fitting (Song & AbouRizk, 2008), [number of bolts, length of weld, length of wide flange beams,…] for structural steel manufacturing (Hu et al., 2015), and [nominal height, weight, and width, concrete volume, finishing area, reinforcement weight, concrete strength,…] for precast concrete production (Benjaoran et al., 2004); (2) worker-related factors such as the number of workers (Benjaoran et al., 2004), and skill level (Song & AbouRizk, 2008); (3) material-related factors such as length and weight (Hu et al., 2015; Song & AbouRizk, 2008); (4) machine-related factors such as breakdowns and interactions of material handling systems (Song & AbouRizk, 2008); (5) factory operations-related factors such as work shift (Song & AbouRizk, 2008); and (6) production line-related factors such as activity precedence relationships, queuing, and rework (Song & AbouRizk, 2008). Finally, a list was compiled for 36 classified factors of which the cycle time at the case framing workstation may be a function. These factors are listed in Table 1 below. It should be noted that certain factors that, although may influence framing cycle time, are highly complex and may require a comprehensive analysis of their own (e.g., worker morale, work environment, worker wellness, pay, etc.) were excluded from the case study. It should also be emphasised that, while there may be factors that influence cycle times at framing workstations in other companies, or in other workstations at the case company, only factors influencing cycle time at the framing workstation under study were considered. For instance, the availability of tools and machines is a commonly encountered factor that influences cycle time, but these resources at the case workstation are not shared with other workstations and, hence, are always available. The input of the operator on these factors (presented in the following section of this paper) helps to further clarify meaning, and provide a preliminary justification for inclusion, for the listed factors.

STAGE III: SOLICIT WORKERS' INPUT ON THE FACTORS

At this stage, the operator's input was solicited (via semi-structured interview) concerning the list of potential factors. The operator consulted, it should be noted, has more than ten years of experience working at the framing workstation at the case company, making him highly knowledgeable about the process. The operator was asked whether or not, why (if applicable), and in what manner (if applicable) each of the listed factors affects cycle time. The operator indicated that some of the listed factors are correlated with other factors, which means that they hold information also held by other factors with regards to cycle time. The interview results are summarised in Table 1 (found in the following subsection), where (✓) indicates that the given factor was considered by the operator to influence framing cycle time, (X) indicates that the given factor was not considered by the operator to influence framing cycle time, and (C) indicates that the given factor was considered by the operator to influence framing cycle time, but that the factor is correlated with another one. The operator's comments included in the table are based on written notes taken during the interview. (It should be noted that the comments as represented are a mix of the exact words of the operator and reformulations of some of the operator's input.) Factors for which no specific comments were made during the interview are denoted by a dash symbol in the "operator's comments" cell in the table.

RESULTS AND DISCUSSION

Based on the interview results, the majority of the factors identified in the first two stages were deemed to be relevant based on the operator's input. Accordingly, it was determined that these factors (highlighted in green in Table 1) should be left for the machine-learning process. During the semi-structured interview, the operator provided information that directly resulted in the exclusion of previously included factors, as it became evident based on this information that these factors (highlighted in red in Table 1) do not influence framing cycle time. Removing these factors would help to avoid unnecessary effort expended collecting data on factors that would have been removed during the machine-learning process anyway, as well as reducing the complexity of the machine-learning process. However, factors with respect to which workers may make subjective judgements were not excluded (even when flagged as candidates for exclusion) unless the machine-learning process confirms their irrelevance. For instance, the hypothesis underlying the wall panel design complexity factor is that it may take the operator more time to interpret the shop drawings and load the elements accordingly for more complex wall panels (since they typically require more framing tasks compared to less complex wall panels). Even though the operator indicated that this factor does not affect the time it takes to frame a panel, relying solely on their experience-based input may introduce bias, as it is difficult to assess how long it takes to interpret a shop drawing or load elements from different locations without a quantitative analysis. As such, these factors (highlighted in orange in the table) should be examined in the machine-learning process. Moreover, the operator identified two factors as being correlated with other factors. One of these was panel length (highlighted in yellow), which was indeed found to be correlated with the number of cuts. However, the panel length factor may hold additional information that is not captured by the number of cuts factor or by other factors. In fact, many of the previous studies in this area have used panel length as a factor (as discussed above), further supporting the hypothesis that it is an influencing factor. Additionally, panel length is correlated with the number of holes used for lifting, a consideration that the operator did not mention. This justifies the consideration of panel length as a potential influencing factor, as well as its inclusion in the final list of factors. The other factor identified by the operator as being correlated with other factors was the distance between the nail inventory location and the workstation, this factor being correlated with the nail gun refill factor. Reaching the nail inventory during the process of framing a wall panel was found to be 100% correlated with the nail gun refill factor, and for this reason the former factor can be excluded. Finally, the operator noted that adjusting the machine's opening to accommodate panels of different heights adds an extra step to the framing process for certain panels. Hence, the height difference between a panel and its preceding panel should be examined as an influencing factor. The framing sequence of panels should be also included in the final list of factors to account for any other correlations between cycle times of subsequent panels. Additionally, the operator mentioned that events occurring on certain days may affect productivity (Factor 21). Thus, the framing date should also be considered to better understand cycle times.

Table 1: Results of semi-structured interview

Class	Factors and operator's comments	Effect?
Product	**1. No. of single studs**: -	✓
	2. No. of double studs: "They take more time to nail than single studs as they require more nails."	
	3. No. of L-shaped studs: "They also take more time to nail than single studs as they require more nails."	
	4. No. of multi-ply studs: "They take more time to nail than the previous three types of studs, and they take more time to nail with every additional ply."	
	5. No. of regular doors: "They could take about 6 times longer to nail single studs."	
	6. No. of large doors: "They could take about 10 times longer to nail single studs."	
	7. No. of garage doors: "I need to do some manual work for garage doors, so they	

	take much longer than large doors." **8. No. of regular windows**: "They could about 6 times longer to nail single studs." **9. No. of large windows**: "They could take 10 times longer to nail single studs." **10. No. of cuts**: "Cutting takes about as long as nailing single studs." **11. No. of drill holes**: "The time needed to drill a hole is close to the time needed to nail single studs." **12. No. of blocks**: - **13. No. of components**: -	
	14. Panel length: "Longer panels typically comprise multiple wall panels that are grouped together. As such, they necessitate a higher number of cuts, but this effect is correlated with the number of cuts per panel."	C
	15. Panel height: "This factor may affect cycle time in two ways. First, for higher wall panels, all panel elements (e.g., stud) are heavier. Whether this factor affects or does not affect cycle time depends on each worker. Some workers may find it harder to lift and load longer elements while other workers may not be affected. Second, I should adjust the machine's width between panels of different heights. This task is not required when a batch of panels of equal height are framed sequentially. Moreover, before I can adjust the machine, I must be able to push the completed panel downstream which means that the downstream station must be available. This task adds additional time to the cycle time for certain panels."	√
	16. Panel thickness: "A thicker panel is composed of thicker elements (e.g., 2×6 studs versus 2×4 studs). First, thicker elements are heavier and may be more difficult to lift and load. Second, thicker elements require a larger number of nails."	√
	17. Availability of shop drawings: "Shop drawings are always made readily available before they are needed."	X
	18. Wall panel design complexity (It reflects the variety of framing tasks that the operator must complete for a wall panel): "Aside from the varying time required by each type of element (e.g., single stud versus door), having a panel composed of single studs only versus a panel with a mix of various elements does not affect cycle time as the same steps are followed to load each element and run the machine."	X
	19. Quality of shop drawings (i.e., dictates the frequency of errors + delay + rework time if any): "This factor has a high impact on cycle time. The framing machine cannot read drawings with errors. As a result, I have to stop the work, inform the drafter, and wait for the revised draft before work can be resumed."	√
	20. Work shift (i.e., morning vs. afternoon) (which could relate to fatigue): "This may have an effect, but it depends on each worker and the workstation. For instance, younger workers may work faster at the beginning of the day and start slowing down throughout the day. Meanwhile, older workers may be more consistent in their speed throughout the day. Moreover, when the workstation is semi-automated, the worker's pace may be dictated by the machine's pace, which increases consistency. Sometimes, however, random events may happen throughout the day, and workers could become mentally drained in the afternoon."	√
Worker	**21. The day of the week (which could relate to work motivation or fatigue accumulation)**: "Monday mornings may be less productive as workers return from weekends, which may involve disrupted sleep schedules, alcohol, etc. Tuesdays are more productive as workers become dialled in. Thursdays (given that the company has a four-day work week) may be also productive because workers are motivated to finish their work earlier and start their weekend. Regarding fatigue accumulation, this factor may be more critical in the summer as workers get tired more quickly in higher temperatures and may get less rest after work. This means that their bodies may recover less between workdays, which may lead to fatigue accumulation."	√
	(Note: the operator's comment on this factor was generic and is not applicable to the case workstation given the operator's long years of experience.	X

	22. Learning curve: "This factor has a high impact on cycle time, but it varies among workers. Some workers are fast learners and retain knowledge, while others constantly seek help from others, thereby increasing cycle times."	
Machine	**23. Breakdowns**: "Some breakdowns result in complete work stoppages while others may only cause minor interruptions. For instance, the nail gun may occasionally shoot double nails, requiring extra work to cut the defective nails each time it occurs. Although this extends the framing process, it does not entirely halt production. These issues may occur approximately once every two weeks. In contrast, machine failures that require complete shutdown may last anywhere from 15 minutes to an entire day, and may occur approximately once every six months.	√
	24. Errors: "The machine may result in errors (e.g., nailing defect); a couple of minutes may be spared per incident."	√
	25. Nail gun refills: "The machine's nail gun was replaced with a new one of a different brand, but the new one must be refilled more frequently. Nail refills add more time to the cycle time for certain panels."	√
	26. Motion speed: "The machine has a constant motion speed."	X
Material	**27. Material type**: "Different types of materials (e.g., Laminated strand lumber (LSL) versus Spruce wood) vary in weight (e.g., LSL is heavier than Spruce), and heavier elements may be more difficult to lift and load."	√
	28. Delays in raw material supply: "There are no delays related to raw material supply."	X
	29. Delays in material preparation activities (e.g., sub-assembling door openings): "Material preparation activities are completed one shift or half a shift before the material is needed."	X
Workstation setup	**30. Distance between material inventory location and installation location**: "I must reach the nail inventory location every time a nail gun refill is needed, but this factor is correlated with the "nail gun refills" factor. All the other materials are reachable from my work location."	C/X
	31. Distance between tools location and workstation: "All the tools are located in a way that I can reach them without travelling."	X
Production line	(Note: the framing workstation is the first workstation on the wall production line) **32. Delay at downstream workstations**: "While waiting for the downstream workstation, I could start setting up the machine for the following panel instead of standing idle."	√
Factory operations	**33. Workload – Sq. Ft. per day**: "If the workload is low, the workers may become slower. Meanwhile, high workload may have two outcomes depending on the worker; while some workers may become faster trying to finish the scheduled work during working hours, other workers may become overwhelmed with the increased workload which, in turn, adversely affect their productivity."	√
	34. Overtime shift: "It depends on each worker. My speed during overtime shifts and regular shifts is consistent if overtime shifts are occasional."	X
	35. Weekly cumulative overtime: "In case of multiple overtime shifts during a week, workers do not have enough time to recover and become less productive."	√
External factors	**36. Ambient temperature**: "When the temperature exceeds 20 °C, workers get tired more quickly and become slower since there is no air conditioning in the factory."	√

Following this approach, the modeller will have a set of factors that are highly likely to influence cycle time at a given workstation (highlighted in green), another set of factors that are likely to influence cycle time (highlighted in orange and yellow), and a third set of factors that show minimal or zero likelihood of influencing cycle time (highlighted in red). The modeller will also have a good understanding of how these factors could influence cycle time and, hence, will be better positioned to rationally interpret the performance and the results of a machine-learning model developed to predict cycle times at the workstation under study. This facilitates the development of prediction models that more accurately capture the complexity of the process under study. It is important to note that not all influencing factors will become part of the prediction model. Some factors may be excluded due to various reasons such as data unavailability, an insufficient sample size, or weak correlations with cycle time compared to other factors. The modeller will nevertheless have an awareness of the potential effect of the excluded factors on the results. To further demonstrate the importance of following such a systematic approach for identifying influencing factors, let us consider a brief overview of the results obtained for building a model that predicts processing times (excluding delay times) at the case framing workstation. A multi-layer feedforward artificial neural network model was trained and cross-validated (using a 10-fold cross-validation) using data collected on 172 wall panels framed at the case framing workstation. The case company estimates the capacity of the workstation in linear meter per minute (m/min), so only panel length was used as a predictor variable in the first model. Based on cross-validation results, the mean absolute error was found to be 2.18 min. Adding the geometric properties of the given panel (i.e., Factors 1–16 in Table 1) reduced the error to 1.94 min, resulting in an 11% reduction in the error. Moreover, considering the complexity, day, shift, temperature, height difference, framing sequence, and date factors further reduced the error to 1.80 min, resulting in a total error reduction of 17%. The details of this neural network model are not presented in this paper due to space limitations, but will be presented in a future paper. Nevertheless, this brief overview of the results serves to highlight the value of dedicating time and effort to identifying and understanding the factors that influence process cycle time; Having a comprehensive pool of influencing factors is vital for the development of more accurate prediction models. As such, following the same approach for identifying influencing factors and building prediction models for different workstations, the modeller gains a deeper understanding of what factors drive cycle time variability and becomes well positioned to analyse cycle times across workstations. This, in turn, can facilitate workload balancing across workstations to ensure leaner operations.

CONCLUSIONS

This paper presented a structured approach for identifying and understanding the factors influencing cycle times at workstations in offsite construction factories, an essential step toward more accurate analysis of cycle times across workstations for the purpose of balancing production lines. The application of the approach was demonstrated in reference to a semi-automated, wood-wall framing workstation in a panelised manufacturing factory in Edmonton, Alberta, Canada. A total of 36 potential factors categorised into eight classes were identified based on observation, a cross-functional diagram of the process, and a literature review. These factors were further investigated based on the input of the workstation operator solicited in a semi-structured interview, and the factors were further discussed in light of the interview results. A brief demonstration of their effect on the performance of an artificial neural network model was presented, where using more factors as prediction variables in the model reduced the mean absolute error by 17%. A detailed description of the neural network model will be presented in a future paper. In short, this study demonstrated the value of expending effort on the identification and understanding of the factors influencing cycle times at workstations in offsite construction. Doing so can be expected to aid in streamlining and improving the accuracy of cycle time analysis for the purpose of applying *Heijunka* and balancing production lines, thereby minimising instances in which workers find themselves playing the role of the “hare”.

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