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SIMULATION-AIDED ASSESSMENT OF TEAM PERFORMANCE: THE EFFECTS OF TRANSIENT UNDERACHIEVEMENT AND KNOWLEDGE TRANSFER

Yaileen M. Méndez-Vázquez

Department of Mechanical Engineering
Milwaukee School of Engineering
1025 N Broadway
Milwaukee, WI 53202, USA

David A. Nembhard

Department of Industrial Engineering
Oregon State University
2000 SW Monroe Ave
Corvallis, OR 97331, USA

Mauricio Cabrera-Rios

Department of Industrial Engineering
University of Puerto Rico, Mayaguez
P.O Box 9000, Calle Post
Mayaguez, PR 00681, USA

ABSTRACT

Many organizations have considered implementing teamwork as an approach to improve organizational performance and boost the learning process of workers. Despite the benefits offered by teamwork, literature has also shown negative aspects of this kind of work setting, including the transient initial team underachievement known as process loss. Studies have been dedicated to investigate the effect of implementing teamwork strategies on team productivity. However most of these studies remain observational in nature, partially due to the complexity associated with performing physical experimentation in teamwork manufacturing settings and the study of human cognition. The current study proposes the use of simulation as a strategy to conduct experimentation in this kind of setting. This work capitalizes on simulation to investigate the joint effect of knowledge transfer and process loss on team productivity for manufacturing settings. The joint effect of these factors on team productivity still remains unknown in current literature of teamwork.

1 INTRODUCTION

The implementation of work teams is a common and attractive strategy for managers across academic, manufacturing and service organizations. The implementation of work teams in organizations has been linked to many benefits including but not limited to dividing up workload, learning from knowledge sharing, founding a collaborative environment, amplifying individual perspective, and incrementing organizational expertise (Cross 2000; Drach-Zahavy and Somech 2002; Baeten & Simons 2014). Recently, attention has been paid specifically to the process of knowledge transfer between workers at team and organizational levels (Reagans et al. 2005; Knockaert et al. 2011; Baeten & Simons 2014; Glock & Jaber 2014; Nembhard & Bentefouet 2015; Jin et al. 2018). Knowledge transfer is defined as a human cognitive process wherein individuals use knowledge accumulated by other team members in order to improve their individual performance. (Reagans et al. 2005; Nembhard & Bentefouet 2015).

However, despite the benefits associated with the implementation of work teams and the effect of knowledge transfer between workers within teams, the literature has also shown some negative consequences within team-based work settings, such as a transient initial underperformance known as process loss (Steiner 1972; Erez and Somech 1996; Mueller 2012; Staats et al. 2012; Peltokorpi and Niemi 2018). Formally, process loss is defined as a phenomenon in which the team's actual productivity falls below the team's potential productivity as a consequence of factors including coordination, motivation and relational processes between members (Steiner 1972; Mueller 2012; Staats et al. 2012; Peltokorpi and Niemi 2018). Extensive research has been dedicated to exploring the different factors affecting team performance (Erez and Somech 1996; DeMatteo et al. 1998; Drach-Zahavy and Somech 2002; Doolen et al. 2003; Ogot & Okudan 2006; Mueller 2012; Jaca and Viles 2013; Peters and Carr 2013; Peltokorpi and Niemi 2018), recognizing that the effect of each factor varies depending on the type of task and the work setting in which the teamwork system is applied (Steiner 1972; Doolen et al. 2003; Ogot & Okudan 2006; Jaca and Viles 2013). Consequently, studying the design of teamwork has become vital to 1) understand the factors that affect team performance in a given work setting and 2) look for strategies that support team design to allow organizations maximize the benefits from a teamwork strategy implementation.

This study uses simulation as a tool to explore the effect of process loss and knowledge transfer on team performance when designing and implementing teamwork strategies in manufacturing settings. Most existing literature related to work teams focuses on exploring factors that cause process loss or knowledge transfer individually. The joint impact of process loss and knowledge transfer on team performance is less clear when considering a teamwork strategy in an manufacturing settings.

Designing and conducting physical experimentation is challenging even when investigating a small number of factors. When conducting experimental designs with human and teams the challenges and complexities associated with designing and conducting physical experimentation increase as result of the number of replicates, number of participants and coordination required for execution, and statistical confidence purposes. Simulation provides an alternative to actual experimentation.

The current study investigates the joint effect of knowledge transfer and process loss on team performance in manufacturing settings. The study is developed through a series of simulations considering a single team-based work setting and four controllable experimental factors: degree of process loss, degree of knowledge transfer, workforce heterogeneity, and team size. Research has linked the effect of process loss and knowledge transfer as a function of the number of workers in the team (Thomas & Fink 1963; Steiner 1972; DeMatteo et al. 1998; Mueller 2012; Nosenzo et al. 2015; Peltokorpi and Niemi 2018). Similarly, literature related to teamwork has highlighted the effect of workforce heterogeneity as significant on team performance (Steiner 1972; DeMatteo et al. 1998; Drach-Zahavy and Somech 2001; Shafer et al. 2001; Hamilton et al. 2003; Peeters et al. 2006; Jaca et al. 2013).

The following research questions are addressed through this work as a key objective of the study: (1) How does optimal team size change for different levels of a) workforce heterogeneity, b) process loss, and c) knowledge transfer when considering a production system composed of an additive task? and (2) What team sizes are best across different levels of Knowledge Transfer and Process Loss? This paper contributes to the literature addressing impacts of knowledge transfer and process loss on team performance and provides insight to guide managers in making decisions about team size selection as part of the team design process.

2 LITERATURE REVIEW

Teamwork in organizations has been linked in the literature to several benefits. In particular, the possibility of collaboration between individuals and the availability of resources to perform a specific task have been highlighted in this regard. Previous studies have argued that the implementation of teamwork in organizations provides individuals with the opportunity to collaborate and learn from one another, helping to attain better task performance as a team (Cohen & Levesque 1991; Esteban & Ray 2001; Doolen et al. 2003; Tohidi & Tarokh 2006; Akinola & Ayinla 2014), as well as improving the individual performance of team members (Reagans et al. 2005; Destré et al. 2008; Davies 2009; Nembhard & Bentefouet 2015; Jin et al. 2018). Although teamwork settings offer significant benefits, previous research has also recognized challenges posed in these settings that cause teams to perform under their potential capacity (Steiner 1972; Esteban & Ray 2001; Peltokorpi & Niemi 2018). This phenomenon is known as process loss (Steiner 1972; Mueller 2012; Halpin & Bergner 2018; Peltokorpi & Niemi 2018). Previous studies have pointed to team size as one factor with a significant impact on the benefits obtained from implementing a teamwork strategy but also on the losses incurred. The number of members in a team is related to the actual capacity the team possesses to perform a task but also to the amount of coordination within the team, the potential loss of motivation of individual team members, and the relational links members should try to establish in order to effectively perform a task (Steiner 1972; Mueller 2012; Peltokorpi & Niemi 2018). These arguments have been a basis for several studies on teamwork aiming to determine the optimal team size in order to maximize the benefits of implementing a teamwork strategy and minimize the effects associated with process loss (Thomas & Fink 1963; Manners 1975; Kameda et al. 1992; Tohidi & Tarokh 2006; Liang et al. 2008; Akinola & Ayinla 2014; Mao et al. 2016).

Despite the efforts of many studies to explore the benefits and costs of teamwork implementations and how design factors relate to team size, the extension of this knowledge to the formulation of mathematical models that address team formation incorporating the team size benefit-cost tradeoff is scarce. In addition, although Safizadeh (1991), Wi et al. (2009), Stroieke et al. (2013), Wi et al. (2015) and Faraset et al. (2016) proposed models to address team formation in organizations, none of these models account for the effects of process loss, knowledge transfer, or team size on the team performance as part of a team formation approach.

Glock and Jaber (2014) conducted the first study to propose a mathematical model accounting for the effects of team size and learning from others within teams based on team productivity. The model considers team member dynamics and the effect of team size through the incorporation of the concepts of "motivation/ability of individuals to share and absorb knowledge" from others within the team and "factor regulating the time delay in transfer of knowledge due to group size for individuals," respectively. Although the model considers the effect of group size on team performance, it assumes that as time increases, the effect of group size on team performance decreases and approaches zero. However, this assumption would not necessarily be met in all cases of work teams. Although some process loss can be overcome through the repetition of working together as a team on a specific task, given improvement of coordination and familiarity processes (Peltokorpi & Niemi 2018), other aspects of process loss, such as individual motivation caused by individual members' perception of rewards/recognition and support, are not necessarily overcome in this way.

Nembhard and Bentefouet (2015) addressed the team formation problem as part of the worker-assignment problem, considering worker interaction through the modeling of team size and learning by knowledge transfer. The study proposed a mathematical model that relates the effect of worker interaction to the individual productivity through the concept of learning by knowledge transfer. The study was conducted using simulation, and was focused specifically on pure serial and parallel manufacturing structures. The study did not account for the effect of process loss as part of the team dynamic and team size.

Further, Peltokorpi and Niemi (2018) proposed a mathematical model that accounts for the effect of workers' interaction within a team on team performance. As part of the estimation of team productivity, the model considers the effect of process loss as a function of team size, wherein as team size increases, the process loss faced by work teams also increases. The model did not account for either individual contribution to the team nor the effect of process loss on individual productivity. The model also did not account for the effect on team performance of knowledge transfer between workers on a team. The study was conducted using physical experimentation with a limited number of replications.

3 METHODOLOGY

The team formation problem is addressed in this work considering heterogeneous workers and an experiential learning environment. We principally employ simulation to examine the effects of four factors, the degree of process loss, degree of knowledge transfer, workforce heterogeneity, and team size on team performance, defined as team productivity, measured in output/worker units. The simulation experiment and data used for the study are described below.

3.1 Simulation Scenario

The simulations in this study were constructed using MATLAB™ considering a production system composed of a single repetitive task over a time horizon of 50-time periods. The production system simulated in this work consist of a single additive task, defined as a task where individual contributions are summative. For example, many industrial settings have parallel production structures, where a team of workers can each complete work independently, toward a common goal. Thus, the team performance is determined by the sum of the individual contributions (Steiner 1972).

The simulation model consisted of a production system, wherein the number of tasks within the system was determined by the Team Size. That means, for TS = 1, the production system was defined by one task. For a TS = 2, the production system was defined by two parallel tasks. The simulation model described a worker(s) assigned to a task, wherein the productivity of the worker(s) was simulated considering workers' individual learning parameters, which represent the individual learning capacity of a worker. That means, each worker have a different learning rate and consequently a different productivity rate. Therefore, the worker productivity rate was simulated for the described production system, for a fixed time horizon of 50 time periods. The input for simulating worker productivity rates was referred in this study as worker profile, which contains the values of the individual learning parameters for each worker. The simulation of the individual productivity rates and input data are described in the following sections of this manuscript.

For the experiment, we use a full factorial experimental design with four factors as summarized in Table 1. The explored factors include: Team Size (*TS*) , Workforce Heterogeneity (*WH*), Degree of Knowledge Transfer (*KT*), and Degree of Process Loss (*DL*). A total of 450 experimental runs were evaluated, considering 50 replications for each experimental treatment.

For *TS*, six levels were considered ranging from one worker per task, through a six-worker team. The workforce selection for this factor was dependent across the different levels of team size. That is, we treated each additional worker as a marginal increment from the smaller team instance. For example, when *TS*=3, two of the workers are the same as the two workers from *TS*=2. This has the effect of reducing the variance between cases, since we are interested in what happens when we increase or reduce the size of a team, rather than how teams can be assigned more generally, which is itself a complex problem. The specific worker selections are otherwise random. The objective of this type of sampling across the increase of team size is to evaluate whether the incorporation of an additional worker into the work team is beneficial for the specific task, considering the effect of knowledge transfer and process loss on the team performance.

Table 1: Experimental Design.

Factors	**Levels**
TS: Team Size (workers/team)	1, 2, 3, 4, 5, 6
WH: Workforce Heterogeneity (%)	50, 100, 150
KT: Degree of Knowledge Transfer (%)	0, 25, 50, 75, 100
DL: Degree of Process Loss (%)	0, 25, 50, 75, 100

The second factor investigated as part of the study, *WH*, has three levels (Table 1), which represents variances among individual learning parameters. In this study, the workforce heterogeneity was considered by scaling the variance-covariance matrix associated with the probability distribution of the parameters used to construct the workers' profiles (Nembhard & Shafer 2008). The variance-covariance matrix provided in Nembhard and Shafer (2008) was used as a basis, representing the case of *WH* = 1. For the cases of *WH* = 0.5 and 1.5, the variance-covariance matrix used for the case of *WH* = 1 was scaled by a factor of 0.5 and 1.5, respectively, as presented in Table 2. That means, in the scenario of the variance-covariance matrix *WH*=0.5, the workers composing the workforce were more similar with respect to their learning parameters than the workers generated with the variance-covariance matrix *WH*=1.0 and *WH*=1.5. Learning parameters are linked with workers productivity rates (Nembhard & Shafer 2008; Nembhard & Bentefouet 2015). Therefore, workers in the scenario of a variance-covariance matrix *WH*=0.5 are more similar with respect to the productivity rates than the workers generated with the variance-covariance matrix *WH*=1.0 and *WH*=1.5.

Table 2: Variance–Covariance Matrix associated with the Estimation of the Learning Parameters.

***WH* = 0.5 (50%)**	***WH* = 1 (100%)**	***WH* = 1.5 (150%)**
$\Sigma = \begin{array}{rc} \begin{array}{r}\ln k\\ \ln p\\ \ln r\end{array} & \begin{bmatrix}0.73 & 0.34 & 0.34\\ 0.34 & 7.83 & 3.42\\ 0.34 & 3.42 & 4.02\end{bmatrix} \\ & \begin{array}{ccc}\ln k & \ln p & \ln r\end{array}\end{array}$	$\Sigma = \begin{array}{rc} \begin{array}{r}\ln k\\ \ln p\\ \ln r\end{array} & \begin{bmatrix}0.73 & 0.34 & 0.34\\ 0.34 & 7.83 & 3.42\\ 0.34 & 3.42 & 4.02\end{bmatrix} \\ & \begin{array}{ccc}\ln k & \ln p & \ln r\end{array}\end{array}$	$\Sigma = \begin{array}{rc} \begin{array}{r}\ln k\\ \ln p\\ \ln r\end{array} & \begin{bmatrix}0.73 & 0.34 & 0.34\\ 0.34 & 7.83 & 3.42\\ 0.34 & 3.42 & 4.02\end{bmatrix} \\ & \begin{array}{ccc}\ln k & \ln p & \ln r\end{array}\end{array}$

The third and fourth factors, Degree of Knowledge Transfer (*KT*), and the Degree of Process Loss (*DL*), each have five levels. For the Degree of Knowledge Transfer, the first level is for a case with no knowledge transfer, *KT* = 0. In this case, workers cannot benefit from the experience of other team members. For other levels, such as *KT* = 0.25, a worker can benefit from 25% of the experience of other team members. For Process Loss, *DL* = 0, represents the case of zero Process Loss, which is naturally the best in terms of team productivity. Other levels, range up to *DL* = 1, for the case where process loss is severe, and represents the highest team losses reported in the literature to date (Peltokorpi and Niemi 2018). From the data for this worst-case scenario, we estimated the model in equation (1), which passed the goodness of fit test (Chi-square, p = 0.15). Thus, we are able to examine a wide range of process loss conditions by modulating parameter α.

$$TP_W = 9.8358 * \left(\frac{e^{1.0367*TS}}{6.5823+e^{1.0367*TS}}\right) \tag{1}$$

In Eqn. (1), the dependent variable TP_W represents the team productivity, estimated as a function of the team size (*TS*). The best scenario of team productivity is based on the potential productivity of the team, which assumes zero process loss. The total process loss (as a percentage) for each team size and level of *DL* is then obtained using the straightforward scaling in equation (2).

$$PL = \frac{TP_B - [(1-\mathrm{DL})TP_B + \mathrm{DL} * TP_W]}{TP_B} * 100 \tag{2}$$

3.2 Productivity Rate Simulation

The estimation of individual worker performance considers the effects of knowledge transfer and process loss. We adapt a mathematical model described in Nembhard & Bentefouet (2015) which estimates the worker production rate (Y_x) considering the worker's previous experience, represented by the parameter *p*, the amount of cumulative work *x* in a specific task, the steady state level *k* that will be achieved when the worker completes the learning process, and the cumulative production required to achieve a *k*/2 level of performance, represented by the parameter *r*. The parameter *KT* and the variable *T* correspond to the percentage of knowledge transferred from other workers performing similar tasks and the total cumulative knowledge of other workers, respectively. The model described in Nembhard & Bentefouet (2015) incorporates the effects of learning by doing and learning by knowledge transfer in the estimation of the individual worker performance. In team contexts, individual performance can benefit from the available human resources and available knowledge in the team (Thomas & Fink 1963; Reagans et al. 2005; Mueller 2012). However, individual performance can also be negatively impacted as a result of coordination, relational, and motivational processes between team members (Thomas & Fink 1963; Steiner 1972; DeMatteo et al. 1998; Doolen et al. 2003; Ogot & Okudan 2006; Erez and Somech 1996; Mueller 2012;

Staats et al. 2012; Jaca & Viles 2013; Nosenzo et al. 2015; Peltokorpi & Niemi 2018). Literature related to teamwork and process loss lacks a mathematical model that considers the effect of process loss on the estimation of individual productivity. In equation (3) we propose a model which includes the effects of process loss in the estimation of individual worker productivity.

$$y_x = k * (1 - PL) * \left(\frac{KT*T+x+p}{KT*T+x+p+r}\right) \quad (3)$$

The effect of process loss is represented by parameter *PL*, bounded by 0 and 1, which quantifies the percentage of individual productivity that is lost from the need for required coordination, the need to build relationships and communication links with other individuals in a team, and the loss of motivation that results from working in a team context of a specific size. The model assumes a constant level for a given team size.

3.3 Input Data

The input data for the simulation model comprises a set of workers profiles, wherein each worker profile consists of a set of learning parameters (*k, p, r*) for each task. For the current study, the sampling of the parameters for the construction of the workers' profiles was based on Multivariate Normal Distribution (MVND), using as an input the mean vector and variance-covariance matrix described in Nembhard & Shafer (2008), obtained from an empirical dataset of 75 workers.

4 RESULTS & DISCUSSION

A Weighted Least Squares (WLS) ANOVA with main effects and second order interactions was considered to compare the effects of the experimental factors. WLS was used to mitigate heteroscedasticity in the data. The results are shown in Table 3, with the average output per worker as the dependent variable. The corresponding main effects Lots are given in Figure 1, and interaction plots given in Figure 2. Within this additive system, the output represents the sum of the individual contributions of the team members. The selection of the average output per worker as the performance measure for the ANOVA analysis corrects for the scaling of different system sizes explored as part of the factor of Team Size, such that the comparisons are relatable. The ANOVA results show that Team Size, Workforce Heterogeneity, degree of Knowledge Transfer, and the degree of Process Loss each have a significant effect on performance at a confidence level of 95%. All the second order interactions resulted in a significant effect on the performance measure.

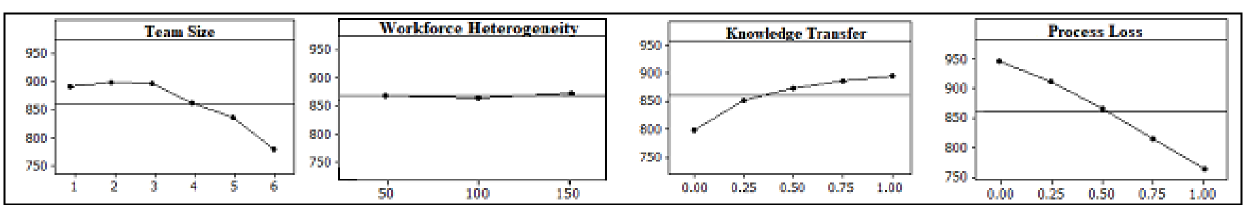

Figure 1: Main Effects Plots of Additive Output.

4.1 Team Size

The Team Size main effects indicate a significant difference in system performance (Table 2, $p < 0.01$). Since there are six levels, we performed a Tukey multiple-comparisons (confidence level of 95%). The multiple-comparisons test showed that each level with the exception of teams of size two and three, differ in performance. Further, team sizes of 2 and/or 3 workers performed better than single assignments and better than teams of 4 or larger. Thus, team size may be a critical decision point in the work design for teams conducting additive work.

The performance differences based on team size, *TS*, are better understood by examining the interactions with *TS*. For the Knowledge Transfer – Team Size interaction, the results revealed that for scenarios where $KT \geq 0.5$, there are some gains from knowledge transfer that translate to small teams (e.g., teams of 2-4) outperforming individuals. That is, working together allows for enough transfer to offset the process losses. In team-based work settings, the impact of knowledge transfer between workers would may team performance, surpassing the impact of team process loss until a maximum team performance *P** is reached for a specific team size *TS**. However, as team size increases beyond *TS**, the impact of process loss surpasses the benefits obtained from knowledge transfer between workers, resulting in the decrease of team performance.

Table 3: WLS ANOVA: Dependent Variable: Output per worker.

Source	DF	SS (adj)	MS (adj)	*F Ratios*	Pr > *F*
Team Size (*TS*)	5	72224.2	14444.8	14127.2	0.00
Workforce Heterogeneity (*WH*)	2	105.1	52.6	51.4	0.00
Knowledge Transfer (*KT*)	4	22612.1	5653.0	5528.7	0.00
Process Loss (*DL*)	4	94004.3	23501.1	22984.4	0.00
*TS*WH*	10	125.8	12.6	12.3	0.00
TS KT*	20	4773.0	238.7	233.4	0.00
TS DL*	20	102606.3	5130.3	5017.5	0.00
WH KT*	8	40.2	5.0	4.9	0.00
WH DL*	8	89.9	11.2	11.0	0.00
*KT * DL*	16	382.4	23.9	23.4	0.00
Error	22402	22905.6	1.0		
Total	22499				

[significance level of 5%; R-Sq (Adj) = 97.3%]

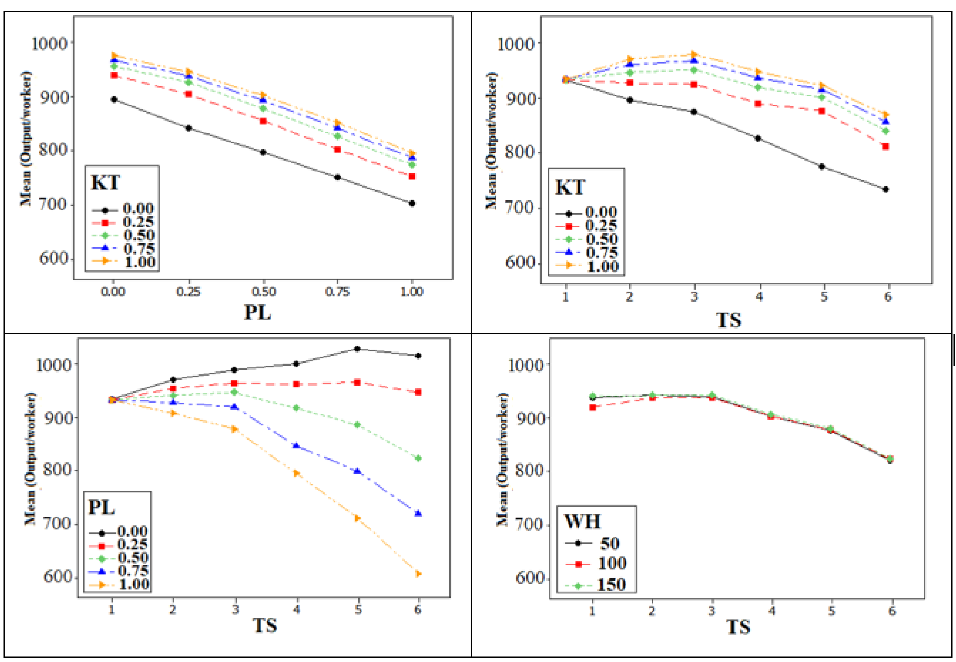

Figure 2: 2-way Interaction Plots.

The Process Loss – Team Size interaction indicates that for *DL*< 0.5, larger teams generally outperform the smaller teams, though in all cases of *DL* except the zero case, the interaction plots suggests that process loss will eventually overcome the gains from knowledge transfer.

The Workforce Heterogeneity – Team Size interaction, while statistically significant, does not reveal a strong relationship. The results from a multiple comparison revealed that for almost all explored levels of the factor Team Size, $TS \geq 2$, team performance in scenarios with lower levels of workforce heterogeneity was not significantly different from team performance in scenarios with higher levels of workforce heterogeneity. We remark that the with regard to workforce heterogeneity, this suggests a general robustness of the team size results as they relate to variations between workers in the workforce.

To summarize the relationship between *KT*, *DL* and *TS*, Figure 3, illustrates the preferred team size by *DL* and *KT*. From the figure is clear that for all but relatively low levels of *KT* and *DL*, a modest team size of 3 is most preferred. When there is little process loss, larger teams make sense due to the positive effects of knowledge transfer.

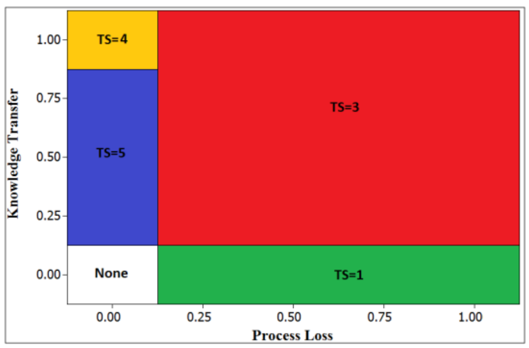

Figure 3: Preferred Team Size (TS) by Levels of Knowledge Transfer (KT) and Degree of Process Loss (DL).

The results regarding Team Size maintain consistency with prior research, where a significant relationship has been highlighted between team size and team performance (Thomas & Fink 1963, Tohidi & Tarokh 2006, Steiner 1972, Mueller 2012, Glock & Jaber 2014, Pieltokorpi & Niemi 2018). Research has established that as team size increases, the availability of human capital to perform a specific task also increases, which can be used for workers in the team to hasten their individual learning process for a task (Nembhard & Bentefouet 2015, Mao et al. 2016, Jin et al. 2018). In particular, individuals in teams can learn from others by observing and interacting with their teammates (Destré et al. 2008, Nembhard & Bentefouet 2015, Mao et al. 2016, Jin et al. 2018). The current results suggest that the benefits obtained by the increase of human knowledge as a result of adding an additional worker to the team exceeds the productivity losses from larger teams. Thus, the selection of team size should not be considered as a straightforward decision within organizations, in order to maximize the benefits obtained through the implementation of a team-based work setting. Studies have attributed this relationship between process loss and team size to issues of coordination, communication, and motivation that arise as more members are added to a team to conduct a specific task (Steiner 1972; Mueller 2012).

4.2 Workforce Heterogeneity

For Workforce Heterogeneity, the ANOVA showed a significant difference in system performance (Table 3). The multiple comparison test for this factors shows that this effect is somewhat small, yet the three levels demonstrate differences, with the highest performance corresponding to the highest level of heterogeneity. This is consistent with the results in both Shafer et al. (2001) & Steiner (1972). However, neither of these studies considered the effect of knowledge transfer within teams in addition to workforce heterogeneity and the effect of process loss. Shafer et al. (2001) investigated the impact of workforce heterogeneity on system throughput, considering the individual worker performance as a function of experience and individual ability to learn by doing. They found that higher levels of workforce heterogeneity in a system defined with independent tasks resulted in a higher system productivity than systems defined with lower levels of workforce heterogeneity. Shafer et al. (2001) suggest that this is because for heterogeneous workers, the faster workers make up for deficits from the slower workers. Steiner (1972) discussed the implications of workforce heterogeneity in team performance, suggesting that in the case of additive tasks, workforce heterogeneity will not significantly impact the potential productivity of the team. From a motivational perspective, workforce heterogeneity can impact the actual productivity of the team, given the individual perception of performance and workload distribution versus rewards. Thus, the current results extend the literature on the exploration of the effect of workforce heterogeneity on system performance to the context of team-based organizational settings, considering the interactions with process loss and knowledge transfer.

4.3 Knowledge Transfer

For Knowledge Transfer, the ANOVA showed a significant difference in system performance (Table 3). To compare the levels investigated as part of the factor of Knowledge Transfer with respect to system performance, a Tukey multiple comparison test was performed. The results showed that for instances which considered full Knowledge Transfer (KT=1), team performance is maximized, and decreases as the level of KT decreases. This ideal condition is unlikely in practice but provides a bound on what is achievable. The current results extend the exploration of the effect of Knowledge Transfer on system performance considering the context of a team-based organizational setting for a production system defined with additive task type structure. (Reagans et al. 2005; Destré et al. 2008; Nembhard & Bentefouet 2015).

4.4 Process Loss

For the degree of Process Loss, the ANOVA showed a significant difference in system performance, wherein it showed the largest impact on the team performance among the factors considered (Table 3). A Tukey-multiple comparison test was performed to compare the difference between the levels investigated as part of the factor Process Loss with respect to system performance. The results of this analysis showed that scenarios with zero process loss are associated with higher team performance (Figure 1). These results suggest the importance of the implementation of strategies to help reduce the effects of process loss in a team-based work environment.

These results are consistent with previous findings in literature related to team dynamics, supporting the credibility of the mathematical expression presented in equation (3) to model workers productivity in a team context. An experimental validation of the model would be valuable as future work. However, this study will serve as a basis for further study of team dynamics from the perspective of team size, knowledge transfer, and process loss, their effects on system performance, and their application to operational research problems, specifically in the area of workforce simulation. Similarly, this study highlights the need for the exploration and development of mathematical models that can account for benefits and drawbacks of teamwork implementation for individual performance. Several studies have discussed the causes and effects of process loss. Erez (1996) examined different causes of process loss, specifically social loafing, concluding that familiarity, clear goal definition, communication, and rewards have an impact on individual performance when working on team-based tasks, and consequently on team performance. Other studies of process loss have mostly focused on the effect of group size on process loss and consequently on team performance (Frank & Anderson 1971; Steiner 1972; Kameda et al. 1992; Mueller 2012; Mao et al. 2016; Peltokorpi & Niemi 2018). None of these studies, however, extend their analysis to explore the actual impacts of process loss on team performance. Moreover, none of these studies extend their exploration to the effect of process loss and knowledge transfer simultaneously, as functions of team size, on team performance.

5 CONCLUSIONS

The purpose of this paper was to explore the effect of team size on team performance, considering jointly the effects of knowledge transfer between workers and team process loss. Previous research has studied the relation between team size and knowledge transfer, arguing that as more workers are added to the team, the available resources the team has to complete the task increases as well. Similarly, previous research has also found a relationship between process loss and team size. Specifically, studies have demonstrated that as team size increases, the gap between the potential productivity and the actual productivity of a team also increases as a result of motivational, relational, and coordination issues that arise within teams. We evaluated the joint effects of knowledge transfer and process loss on team performance, and how decisions related to team size are impacted in production systems define with an additive task type structure. Studies exploring team formation and as well models to estimate individual performance considering the joint effect of knowledge transfer and process losses are notably absent in the literature, specifically for the complexity associated with human-team experimentation.

Therefore, a simulation strategy was implemented to tackle this problem in order to lower the complexity and simplify the design and conduction of experimentation in this kind of setting. As part of the simulation experiment we examined four experimental factors including degree of process loss, degree of knowledge transfer, team size, and workforce heterogeneity. Workforce heterogeneity was considered through the estimation of individual worker productivity as a function of the cumulative experience on the task, the effect of process loss as a function of team size, and the individual capacity for learning by doing and by knowledge transfer. The broad findings of this study are summarized below.

For a production system with additive tasks, Team Size had a significant effect on team performance, highlighting the importance of its consideration as part of a teamwork strategy. The application of a teamwork strategy was shown to be beneficial for team performance in some task scenarios, instead of assigning workers individually to perform tasks, when considering the effect of process loss and knowledge transfer between workers. Nonetheless, the tuning of factors, such as team size selection, that helps to maximize the benefit of this strategy—is not a straightforward decision process. The managerial implications of these findings suggest that with at least a modest amount of knowledge transfer and process loss, a teamwork strategy has a positive effect on productivity. That is, teams of 2-4 may be beneficial in such scenarios, noting that only in the case of zero or near zero process loss, do larger teams have marginal benefits for productivity. This is notable given that additive tasks can be, and often are performed independently in practice. While workforce heterogeneity had a significant impact on team performance, this factor showed a relatively small impact on team performance, indicating the robustness of the team size results across a range of workforce variability. Also, managers might prioritize modeling and consideration of others factors as they relate to team size.

A contribution of the current study is to extend the analysis of team performance given the trade-off between process loss and knowledge transfer in an operation research context. This study explores the impact of different levels of process loss and knowledge transfer on team performance. Previous studies did not consider the interaction between these two factors as part of the team formation problem. The current study will serve as a basis for exploring team dynamics from the perspective of team size, knowledge transfer, and process loss, on system performance and the application of this knowledge to address operation research problems. Similarly, this study highlights the need to explore and develop mathematical models that account for the benefits and drawbacks of teamwork implementation for individual performance. From a managerial perspective, Knowledge Transfer in an additive team setting can hasten the learning process of workers within the team. In some work conditions, the effect can overcome the effects of process loss, making somewhat larger teams preferential. Similarly, managers might consider the development of strategies that facilitates better communication and coordination among team members to make the tradeoffs between these effects more favorable.

The model presented represents a hypothetical case of team context, assuming that in these scenarios, individual worker performance is directly proportional to the effect of process loss. The development of mathematical models, derived from experimental data, that relate the effect of knowledge transfer and process loss to individual worker performance in teamwork contexts remains a gap in the teamwork literature and will be an area of interest for future research. The development of methods to address team formation as part of the worker-assignment problem, considering both process loss and knowledge transfer as results of team dynamics would be a natural extension of the current study..

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AUTHOR BIOGRAPHIES

Yaileen M. Méndez-Vázquez obtained a Ph.D. in Industrial Engineering from Oregon State University. She is Assistant Professor at Milwaukee School of Engineering. Her research interests include experimental design, simulation-optimization and human cognition simulation. Her email is mendezvy@oregonstate.edu.

David A. Nembhard obtained a Ph.D. in Industrial & Operations Engineering from the University of Michigan. He is Professor of Industrial Engineering at Oregon State University. His research interest includes workforce engineering and human cognition. His email is david.nembhard@oregonstate.edu.

Mauricio Cabrera-Ríos obtained a Ph.D. degrees in Industrial and Systems Engineering from The Ohio State University. He is a Professor in the Industrial Engineering Department at University of Puerto Rico – Mayagüez. His research interests include manufacturing optimization and biological data analysis. His email is mauricio.cabrera1@upr.edu. His research group's email is Applied.optimization@gmail.com.