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WORKER GROUPING AND ASSIGNMENT FOR SERIAL AND PARALLEL MANUFACTURING SYSTEMS CONSIDERING WORKERS' HETEROGENEITY AND TASK COMPLEXITY

Yaileen M. Méndez-Vázquez
David A. Nembhard

Human Analytics Lab
Mechanical, Industrial and Manufacturing Engineering School
Oregon State University
Corvallis, OR 97330, USA

ABSTRACT

The present study addresses the grouping-assignment problem of heterogeneous workers for serial and parallel manufacturing configurations considering the worker production rate as a function of learning by doing and knowledge transfer. A simulated experiment is presented for this end, considering the maximization of the system output as the optimization goal, and the system size and tasks heterogeneity as experimental factors. Three heuristic policies are compared based on the heterogeneity of the groups with respect to the individual knowledge transfer parameter. Research related to team formation for manufacturing systems is scarce and often does not considering workers' heterogeneity nor the knowledge transfer. The results highlight the importance of considering workers' heterogeneity for the grouping and assignment of workers. The implications of this study impact the managerial decision-making process related to the grouping and allocation of workers to tasks as part of the production planning.

1 INTRODUCTION

In order to survive in the competitive global market, manufacturing and service industries are motivated to search for more efficient strategies for continuous operational improvement. The productivity of an industry has often been used as a measure of its performance, and in industries in which the production environment is largely composed of manual tasks, the performance of an organization depends to a great extent upon workers' performance and the industry's efficiency in using its workforce resources. Therefore, workforce planning has been a long-standing topic of interest in the field of organizational management, recognizing its importance for the success of an organization. The main idea behind this effort is to identify how to assign the right worker to the right job at the right moment in order to achieve a specific system performance.

It is recognized in the literature that the individual learning capacity of a worker is related to their performance for a specific task. A huge number of models were developed based on this concept, better known as learning curves (Anzanello and Fogliatto 2011). In general, the basis of the theory of learning curves states that the time needed for a worker to perform a task decreases with the experience of repeatedly performing it. This type of learning is better known as learning by doing. Similarly, past studies in the literature have also demonstrated the ability of a person to learn through the interaction with others colleagues. This type of learning is known as knowledge transfer (Thomas-Hunt, Ogden, and Neale 2003; Olivera and Straus 2004; Argote 2013; Nembhard and Bentefouet 2015). While the impact of the individual learning capacity is well recognized in the individual worker performance, workforce planning often does not consider it. Specifically, knowledge related to the workforce planning considering knowledge transfer between workers is scarce. Prior research demonstrated the impact of knowledge transfer in system performance and highlighted the importance of grouping workers for the worker-task assignment process (Nembhard and Bentefouet 2015).

The present study addresses the grouping-assignment problem of heterogeneous workers to tasks of different complexities through the simulation of human learning. The workers' production rate is modeled as a function of the individual worker capacity to learn by doing and knowledge transfer. For this purpose, the model proposed in (Nembhard and Bentefouet 2015) is used, which incorporates the effect of learning by doing and knowledge transfer. This work investigates three essential research questions: (1) Which heuristic policies perform best for the grouping-assignment of heterogeneous workers to tasks of different complexities when production rate is modeled as a function of learning by doing and knowledge transfer? (2) How does the dimensionality of the production system affect the results obtained by the implementation of the different heuristic policies proposed in this study? and (3) How does the consideration of knowledge transfer for the grouping-assignment of workers impact the system performance in different organizational configurations? The relevance of these questions remains in the search for systematic and efficient methods to help organizational managers to make accurate decisions related to the workforce planning in order to achieve a desirable system outcome.

The present work is structured as follows: Section 2 presents a literature of the existing strategies related to the grouping-assignment of workers. Section 3 describes the simulation model, the experimental design, and the proposed heuristic policies for the grouping step. In Sections 4, a discussion of the most relevant results is presented. Finally, the conclusion and further directions are discussed in Section 5.

2 LITERATURE REVIEW

The workforce is one of the most valuable resources that an organization has. The capacity of workers to learn and translate their gained information into performance improvement has a significant impact on the success of an organization. Prior research demonstrated the impact of workers' learning in the system performance and highlighted the importance of considering it for the workforce planning process (Nembhard 2001; Huang et al. 2012).

However, although the impact of the individual learning to the performance of an organization has been well recognized, methods for workforce planning which considers it are limited. Several works were focused on the development of methods to address questions related to workforce planning, considering the heterogeneity of workers based on individual skills and individual task processing times. In Miralles et al. (2008) a heuristic method is proposed to address the worker assignment and balancing problem for an assembly line configuration. In this work, the workers' heterogeneity was considered through the assignment of a constant value that represents the task processing time to each worker in each specific task. Similarly, Blum and Miralles (2011) address the worker assignment and balancing problem for an assembly line configuration using a heuristic approach. The method proposed in this work addresses the workers' heterogeneity by the assignation of specific task processing time for each worker and the consideration of the workers' incompatibility for certain kind of tasks. Mutlu, Polat, and Supciller (2013) proposes a genetic algorithm to address the worker assignment problem for an assembly line structure. In this work, the heterogeneity of workers is addressed considering the workers' skills and a specific task processing time for each individual worker. In Fowler, Wirojanagud, and Gel (2008) different staffing decisions are addressed, including staffing requirement and cross-training level for each worker, considering the heterogeneity of workers based on their general cognitive ability index (GCA). The GCA index is defined as a measure of the worker ability to learn. In these works, the workers' productivity is assumed constant over experience and the individual learning capacity is not considered.

Several works in the literature include the individual learning capacity of workers to address problems related to workforce planning. The most of them only consider the learning by doing, which refers to the improvement in the worker production rate for the gained experience of repeatedly perform a specific task (Nembhard 2001; Corominas, Lusa, and Olivella 2011; Huang et al. 2012; Hewitt et al. 2015; Liu, Wang, and Leung 2016; Valeva et al. 2017). However, in addition to the individual learning process generated as a result of gained experience performing a task repeatedly, previous works proposed the workers' individual capacity to learn by the knowledge acquired from colleagues with whom workers interact. This is better known as learning by knowledge transfer, which proposes that individual performance in a task improves through the interaction and experience of sharing with other people performing similar tasks (Tomas-Hunt, Ogden, and Neale 2003; Olivera and Straus 2004; Argote 2013; Nembhard and Bentefouet 2015). Much of the work related to this topic focuses on understand the factors that affect the knowledge transfer within groups and how to explain the effect of these factors on the performance at both, the individual and group levels.

Although different studies suggest the impact of knowledge transfer between group members on the individual learning process, workforce planning models to address the grouping of workers are scarcest. Safizadeh (1991) and Song et al. (2015) focus on the study of groups dynamic. Safizadeh (1991) present a theoretical framework to guide managers in the design of groups in manufacturing environments. Song et al. (2015) study the impact of different informal network types in a formal organizational structure. Perron (2010) addressed the problem of planning and scheduling work teams considering a specified number of workers with different skills and a set of jobs that need to be completed. The problem is addressed through mathematical programming techniques. In Stroieke, Fogliatto, and Anzanello (2013) the authors address the problem of grouping workers in a production system considering the individual learning characteristics of the workers and the workload balance between the workers who composed the groups as the objective function. However, neither of these works consider the knowledge transfer between workers within the groups.

The work of Nembhard and Bentefouet (2015) is the first work found in the literature that proposes a mathematical approach to address the worker-task allocation problem considering the grouping of workers and the knowledge transfer as part of the approach. This work incorporates the effect of the knowledge transfer in the estimation of the individual workers' performance through a modification of the hyperbolic model proposed in Mazur and Hastie (1978). The authors divided the worker-task allocation process into three stages—selection, grouping, and assignment—where the effect of knowledge transfer took place in the grouping stage. The results obtained in this work demonstrate the significance of considers the grouping of workers as part of workforce planning in order to improve system performance.

The present study addresses the grouping-assignment problem of heterogeneous workers on tasks of different complexities using the mathematical model proposed in Nembhard and Bentefouet (2015). Different organizational treatments will be applied considering task heterogeneity, system dimensionality, and the system structure, in our case limited to pure serial and parallel production systems, as experimental factors. The work examines the grouping-assignment of the workers based on the heterogeneity within groups regarding the individual knowledge transfer parameter. A simulated experiment is used for this end.

3 METHODOLOGY

This work addresses the problem of the grouping and assignment of workers to tasks of different complexities, simulating the workers' performance as a function of the learning by doing and knowledge transfer. A simulated experiment was designed for this end, in which different organizational scenarios were examined. The simulated experiment used the model described in equation (1) to estimate the individual worker performance.

$$y_x = k\left(\frac{\theta * T + x + p}{\theta * T + x + p + r}\right) \tag{1}$$

This model estimates the worker production rate 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 achieved a $k/2$ level of performance represented by the parameter r. The parameters θ and the variable T are related to the percentage of knowledge transferred from other workers performing similar tasks and the total of cumulative knowledge of other workers, respectively. The model parameters were obtained based on an empirical dataset described in Nembhard and Bentefouet (2015). The details of the data and the simulated experimental design are described below.

3.1 Input Data for the Simulation Experiment

In this study, the workers' production rates were calculated based on the model proposed in Nembhard and Bentefouet (2015) which includes the effect of learning by doing and knowledge transfer. In Nembhard and Bentefouet (2015), the authors fit the model presented in equation (1) to an empirical dataset of 75 workers (Shafer et al. 2001), obtaining an average R^2 of 96% and a standard deviation of 2%. Through the fitting process, the authors modeled the parameters associated with equation (1) (k, p, r) using a Multivariate Normal Distribution with a mean and standard deviation presented in Table 1. For the present study, these values were assumed to be associated with a task of 1 unit of complexity and used to estimate the mean parameter values for tasks of different complexities (Table 2-3). A 1:1 relationship between the task complexity rank and mean parameter was assumed (Nembhard 2000). The mean and variance of knowledge transfer parameter θ was modeled by a normal distribution with a mean of 0.644 and a variance of 0.409 (Nembhard and Bentefouet 2015).

Table 1: Mean values and variance–covariance matrix for the estimation of the learning parameters.

$\boldsymbol{\mu}=\begin{bmatrix}\textbf{log k}\\ \textbf{log p}\\ \textbf{log r}\end{bmatrix}=\begin{bmatrix}1.448\\ 1.963\\ 2.0446\end{bmatrix}$	$\sum = \begin{array}{r c} & \begin{array}{ccc} & & \end{array} \\ \begin{array}{r}\textbf{log k}\\ \textbf{log p}\\ \textbf{log r}\end{array} & \begin{bmatrix}0.0045 & 0.0167 & 0.0191\\ 0.0167 & 0.4621 & 0.2443\\ 0.0191 & 0.2443 & 0.1905\end{bmatrix} \\ & \begin{array}{ccc}\textbf{log k} & \textbf{log p} & \textbf{log r}\end{array}\end{array}$

Previous works demonstrated that when the complexity of the task increases, the values of both, the asymptotic steady-state performance level k and the initial performance p decrease (Nembhard 2000). In contrast, in the case of the learning parameter r, when the complexity of the task increases, the value of that parameter also increases (Nembhard 2000). A constant value was assumed for the parameter associated with knowledge transfer θ through the different levels of complexity. This assumption is based on the fact that the parameter θ is multiplied in the equation by the parameter T that represents co-workers' experience in similar tasks, which are already affected by the task complexity. Similarly, for this work, a constant value for the variance of the parameters through the different levels of task complexity was considered.

Table 2: Learning parameters means for the production system composed of 3 workstations.

	WS1	WS2	WS3
$\mu_{LC}=\begin{bmatrix}\log k\\ \log p\\ \log r\end{bmatrix}$	**C_1= 3.5** $\begin{bmatrix}0.1952\\ 0.7102\\ 3.2974\end{bmatrix}$	**C_2=4.0** $\begin{bmatrix}0.0617\\ 0.5767\\ 3.4309\end{bmatrix}$	**C_3=4.5** $\begin{bmatrix}-0.0561\\ 0.4589\\ 3.5487\end{bmatrix}$
$\mu_{HC}=\begin{bmatrix}\log k\\ \log p\\ \log r\end{bmatrix}$	**C_1=2.0** $\begin{bmatrix}0.7549\\ 1.2699\\ 2.7377\end{bmatrix}$	**C_2=4.0** $\begin{bmatrix}0.0617\\ 0.5767\\ 3.4309\end{bmatrix}$	**C_3 =6.0** $\begin{bmatrix}-0.3438\\ 0.1712\\ 3.8364\end{bmatrix}$

Table 3: Learning parameters means for the production system composed of 9 workstations.

	WS1	WS2	WS3	WS 4	WS5	WS6	WS 7	WS8	WS9
μ_{LC}	**C_1= 3.5** $\begin{bmatrix}0.1952\\0.7102\\3.2974\end{bmatrix}$	**C_2=3.64** $\begin{bmatrix}0.1560\\0.6710\\3.3366\end{bmatrix}$	**C_3=3.76** $\begin{bmatrix}0.1236\\0.6386\\3.3690\end{bmatrix}$	**C_4= 3.88** $\begin{bmatrix}0.0922\\0.6072\\3.4004\end{bmatrix}$	**C_5=4.0** $\begin{bmatrix}0.0617\\0.5767\\3.4309\end{bmatrix}$	**C_6=4.12** $\begin{bmatrix}0.0321\\0.5471\\3.4605\end{bmatrix}$	**C_7= 4.24** $\begin{bmatrix}0.0034\\0.5184\\3.4892\end{bmatrix}$	**C_8=4.36** $\begin{bmatrix}-0.0245\\0.4905\\3.5171\end{bmatrix}$	**C_9=4.5** $\begin{bmatrix}-0.0561\\0.4589\\3.5487\end{bmatrix}$
μ_{HC}	**C_1=2.0** $\begin{bmatrix}0.7549\\1.2699\\2.7377\end{bmatrix}$	**C_2=2.5** $\begin{bmatrix}0.5317\\1.0467\\2.9609\end{bmatrix}$	**C_3 =3.0** $\begin{bmatrix}0.3494\\0.8644\\3.1432\end{bmatrix}$	**C_4=3.5** $\begin{bmatrix}0.1952\\0.7102\\3.2974\end{bmatrix}$	**C_5=4.0** $\begin{bmatrix}0.0617\\0.5767\\3.4309\end{bmatrix}$	**C_6 =4.5** $\begin{bmatrix}-0.0561\\0.4589\\3.5487\end{bmatrix}$	**C_7=5.0** $\begin{bmatrix}-0.1614\\0.3536\\3.6540\end{bmatrix}$	**C_8=5.5** $\begin{bmatrix}-0.2567\\0.2583\\3.7493\end{bmatrix}$	**C_9 =6.0** $\begin{bmatrix}-0.3438\\0.1712\\3.8364\end{bmatrix}$

3.2 Simulation Experimental Design

The simulated setting in this study was constructed in Matlab and consisted of two organizational structures, a pure parallel and a serial production system. The simulated setting considered a time horizon of 100 time periods and 200 replications. An initial pool of workers' profiles was generated as previously described, where each worker profile consisted of a set of learning parameters (k, p, r, θ) for each different task. The size of the initial pool was determined by the total number of tasks that composed the production line considering specialized workers. The factors and levels associated with the experimental design are presented in Table 4 and are discussed below.

In the experimental design, three independent factors were evaluated: Task Heterogeneity (TH), System Size (SS) and Grouping Policies which corresponded to the structure of the groups (GP). For the factor of Task Heterogeneity (TH), two experimental levels were considered. The first level was the case of low variability between task complexities, where the complexities of the workstations were in a range of 3.5 - 4.5 units. The second level of this factor was the case of high variability between task complexities, where the complexities of the workstations were in a range of 2.0 – 6.0 units. Each workstation was characterized by a different complexity, considering the case of heterogeneous tasks. The complexity value assigned to each workstation was used to generate the parameters of the worker profiles corresponding to each specific workstation (Table 2-3).

Table 4: Simulation Experimental Design.

Factors	**Levels**
Task Heterogeneity	Low (3.5-4.5), High (2.0-6.0)
System Size (# Workstations)	Low (3 workstations), High (9 workstations)
Grouping Policies	P_1: Minimization within group variance of θ
	P_2: Maximization within group variance of θ
	P_3: Random grouping with respect to θ

For the second factor considered in this study, system size (SS), two experimental levels were considered. A production line composed of three workstations was evaluated as the first level, and a production line composed of nine workstations as the second level. Each workstation was composed of three tasks, where a specialized worker was assumed for each task. As a result of this configuration, an initial pool of 9 worker profiles was generated for the case of the production line composed of three workstations, and 27 worker profiles for the case of nine workstations. The main objective of the examination of this factor was to investigate the effect of the dimensionality on the system performance. Finally, the third factor considered as part of the experimental design for the present study was the grouping policies (GP). This factor addresses the decision-making process of how organize workers in groups with the aim of maximizing the transfer of knowledge between workers performing similar tasks.

For this factor, three experimental levels are considered. The first level is represented by the heuristic policy P1 and is based on the construction of groups with the lowest variance of the θ parameter between the workers in the workstation. The policy P1 represents a variance minimization approach with respect to the transfer parameter θ. The second level for the factor GP is represented by the heuristic policy P2 and is based on the construction of groups focused on a variance maximization approach with respect to the θ parameter of the workers. Finally, the third level of the factor GP is represented by the grouping policy P3. The policy P3 is based on the grouping of workers in a random way with respect to the θ parameter. The incorporation of the level P3 to the factor of GP intends to examine the impact of the consideration of the knowledge transfer capacity of the workers for the grouping and worker-task allocation. A discussion of the used methodology for the grouping heuristic policies is presented below.

3.3 Grouping Heuristic Policies

The heuristic policy P1 (*minimization approach*) was constructed based on sort and split techniques of the θ parameter values for the available workers, doing the grouping and assignment process simultaneously. The strategy is described as follows: (i) A pool of TA*N worker profiles, generated based on the factors and distribution of parameters previously described, is defined as an input matrix, where N represents the total number of workstations in the system and TA the number of tasks that compose each workstation. For this work, we considered the case in which each workstation is composed of three tasks (TA=3). (ii) The workers' profiles are sorted in descending order based on the θ parameter value. (iii) The three workers with the highest value of θ are assigned to the tasks with the highest complexity rank. (iv) The profiles corresponding to the workers assigned in the previous step are deleted to update the pool of workers' profiles. The experiment considered specialized workers, where each worker is assigned to a unique task during the complete time horizon, and all tasks have one assigned worker in each time period. (v) The worker profiles that remain in the pool are sorted in descending order based on the θ parameter value. (vi) The three workers with the highest values of θ are assigned to the workstation that follows in complexity rank. (vii) The pool containing the workers' profiles is updated. (viii) The method iterates (steps ii-viii) until each workstation has the necessary workers assigned, in our case 3 workers for each workstation.

The construction of the heuristic policy P2 (*maximization approach*) was based on a greedy approach. The strategy is described as follows: (i) A pool of TA*N workers' profiles is defined as an input matrix, as previously described. (ii) The workers' profiles are sorted in descending order based on the θ parameter values. (iii) The worker with the highest value of θ is assigned to the workstation composed of the most complex tasks. (iv) The profile corresponding to the assigned worker in the previous step is deleted to update the workers' pool. (v) The workers' profiles that remain in the pool are sorted in ascending order based on the θ parameter. (vi) The worker with the lowest value of θ is assigned to the second task in the current workstation. (vii) The pool that contains the workers' profiles is updated. (viii) The variance is calculated across the θ parameter values of workers who were currently assigned to the workstation with each worker remaining in the pool. (ix) The worker in the pool who completes the group in the workstation with the highest variance is assigned as the third worker to the current workstation. (x) The workers' pool is updated. (xi) The method iterates (steps ii-x), prioritizing the workstations by decreasing order of rank complexity until all workstations have assigned the necessary number of worker, in our case 3 workers for each workstation.

4 RESULTS AND DISCUSSION

The grouping stage was developed through the implementation of the different proposed heuristic policies described in Section 3 of this work. The ANOVA for the evaluation of the simulation treatments of both parallel and serial production systems are presented in Table 5. For this analysis, the system output was considered as the dependent variable. The independent factors were task heterogeneity, system size, and grouping policies, which showed a significant effect for both production scenarios at a confidence level of

95% (Table 5). This means that all of the analyzed factors in this work, represent a significant source of variability in the performance of the production system for parallel and serial configuration.

Table 5: ANOVA for the simulated treatments (dependent variable: system output).

Source		Parallel System				Serial System			
	d.f	SS	MS	F	P	SS	MS	F	P
TH	1	48083213	48083213	37723	0.00	2060331	2060331	20482	0.00
SS	1	1014630841	1014630841	796018	0.00	1623	1623	16	0.00
GP	2	363292	181646	142	0.00	43251	21626	215	0.00
TH*SS	1	3431388	3431388	2692	0.00	1245	1245	12	0.00
TH*GP	2	155298	77649	60	0.00	1984	992	9	0.00
SS*GP	2	49932	24966	19	0.00	767	384	3	0.02
Error	2390	3046370	1275			240409	101		
Total	2399	1069760333				2349611			

[This analysis was performed using a Generalized Linear Model with a significance level of 5%.]

In terms of the grouping of workers, the results state the importance of the grouping factor for the assignment of workers to tasks in order to maximize system output, where for the serial production system the grouping factor took the second position in the explanation of total variability with respect to the others factors. These results coincide with findings found in Nembhard and Bentefouet (2015), where was demonstrated the significance of the grouping and assignment stages for the system performance. In order to investigate the grouping composition that enhances system performance for different organizational scenarios, three heuristic policies for grouping workers were examined in this work. The first heuristic policy P1 was based on a variance minimization approach with respect to the transfer parameter θ between the workers in a group. The second policy P2 was based on a maximization approach with respect to the transfer parameter θ. Finally, the third heuristic policy P3 was based on the grouping of workers in a random way with respect to the θ parameter. The policy P3 was examined in order to compare if the consideration of the knowledge transfer parameter θ for the grouping of workers (P1, P2) shown a significant difference with respect to the grouping of workers without considering it.

Figures 1 and 2 illustrate the main effect of each of the experimental factors for the cases of serial and parallel production systems, respectively. For the factor of grouping policies (GP), the heuristic policy P1 was favored for the case of the serial production system (Figure 1). This means that for the case of serial production system the grouping of more similar workers with respect to their capacity for learning by knowledge transfer presented a better performance when the system output was considered as a performance measure. In contrast, for the case of the parallel production system, the grouping policy P2 performed best, favoring in this way groups composed of more dissimilar workers with respect to the θ parameter (Figure 2). In order to examine the significance of differences in levels for the grouping policy, a multiple comparison test was performed using the Tukey test with a confidence level of 95%. The results obtained in this test showed that the policy which performed best in each case, P1 for the serial production system and P2 for the parallel production system, had a difference statistically significant with respect to the other two policies at the specific confidence level of 95%. Through these results is shown the significance of considering the knowledge transfer for the grouping-assignment of workers in tasks of different complexities with respect to the implementation of a random policy where the capacity of learning by knowledge transfer was not considered, P1 vs P3 for the serial production system and P2 vs P3 for the parallel production system.

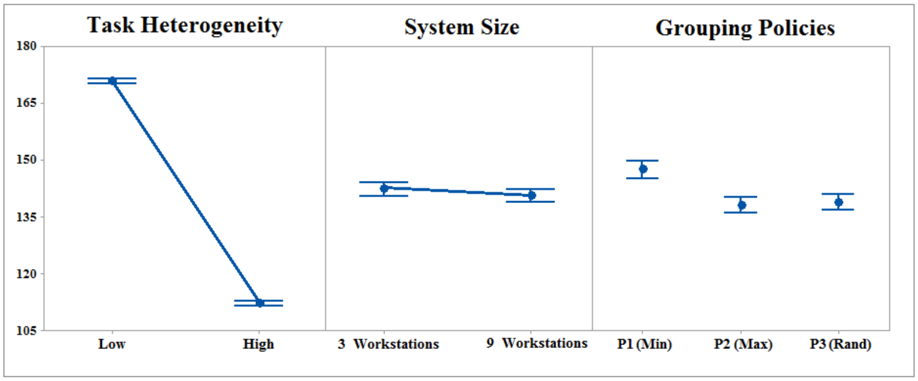

Figure 1: Main effects for the Serial System.

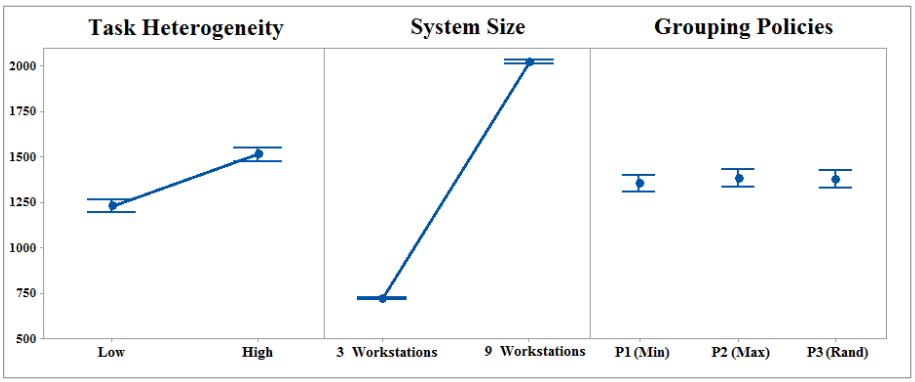

Figure 2: Main Effects for the Parallel System.

Given the experimental results previously discussed, an interest emerged to examine and explain why the heuristic policy P1 and P2 performed best for the case of serial and parallel production system respectively. For this purpose, an analysis of the variation within groups was performed. For this analysis, the data was split by system size and grouping policies, considering the output of each group as a dependent variable. The independent variables were the task heterogeneity and the group's number, where the group number was associated with the task complexity (higher values of group number represent a higher level of complexity in the tasks that composed the workstation).The results showed a significant effect of the new factor defined as group number (GN), which is associated with the complexity rank for each workstation (Tables 6 and 7).

The main effect for the factor GN was shown in Figures 3 and 4 for each dataset previously described. In these figures is showed that for both cases, the grouping policy P2 perform best for the lower levels of the factor GN, but while the group number increases, the policy P1 overpass P2 in term of group output. Figures 3 and 4 show a non-linear decreasing behavior in the relationship between the group number and system output. These results suggest that as the complexity of task increases, the reduction in productivity as a consequence of complexity becomes lesser. This observed effect is supported by Shafer, Nembhard, and Uzumeri (2001), who investigated the impact of worker heterogeneity in the total output. Two scenarios were compared, the first in which all the workers presented the same performance rate, and the second in which an equally distributed variability in worker performance rate was introduced. The results indicated that high heterogeneity between workers resulted in a greater level of total output. The authors explained that these results were obtained due to the fact that the effect of slower workers is not canceled by the effect of faster ones.

Table 6: ANOVA for the within-group variation analysis for the system composed of 3 workstations.

Source		Grouping Policy P1			Grouping Policy P2			Grouping Policy P3		
	d.f.	SS	MS	P	SS	MS	P	SS	MS	P
TH	1	1269068	1269068	0.00	1559269	1559269	0.00	1483872	1483872	0.00
GN	2	9634186	4817093	0.00	13000713	6500356	0.00	12621770	6310885	0.00
TH*GN	2	5853417	2926709	0.00	6387998	3193999	0.00	6261247	3130623	0.00
Error	1194	251023	210		221563	186		280040	235	
Total	1199	17007694			21169543			20646928		

[The analysis was performed considering the system output as the dependent variable at a significance level of 5%.]

Table 7: ANOVA for the within-group variation analysis for the system composed of 9 workstations.

Source		Grouping Policy P1			Grouping Policy P2			Grouping Policy P3		
	d.f.	SS	MS	P	SS	MS	P	SS	MS	P
TH	1	1185724	1185724	0.00	1611054	1611054	0.00	1510279	1510279	0.00
GN	8	13843673	1730459	0.00	21599663	2699958	0.00	20657989	2582249	0.00
TH*GN	8	8934241	1116780	0.00	10203966	1275496	0.00	9954803	1244350	0.00
Error	3582	599578	167		575848	161		732211	204	
Total	3599	24563216			33990531			32855282		

[The analysis was performed considering the system output as the dependent variable at a significance level of 5%.]

To compare the means of each group, a Tukey test was performed with a confidence level of 95%. The test revealed that when we analyze the groups by the grouping policies, the means of the groups are statistically different. Some groups corresponding to the implementation of policies P1, P2 and P3 overlaps in the workstations with middle values of complexity, demonstrating that at this point do not exist an significant difference in the implementation of any of these policies. The second factor which was analyzed in the present study was the tasks heterogeneity with respect to the task complexities. The ANOVA presented in Table 5 shows that for the linear term corresponding to the factor of task heterogeneity, a significant effect on the system output was obtained for the serial and parallel production systems. Two level of this factor were examined in the present study, low and high task heterogeneity respectively.

When the organizational scenarios of low and high task heterogeneity are compared in a serial production system configuration, a greater mean value of the system output was observed for the scenario of low task heterogeneity (Figure 1). In serial production systems, the output is determined by the slowest workstation, which represents the bottleneck of the production line. For the scenario of high task heterogeneity, the slower task has a complexity rank of 6, while the slower task for the scenario of low task heterogeneity has a value of 4.5. Considering that the complexity of a task is associated with its standard time, the execution of the slower task in the case of high TH requires more time in comparison with the slower task in the low TH case. Therefore, more units will be produced in the system associated with the LC case. In contrast, for the case of the parallel production system, an opposite effect for the tested organizational scenarios was observed. In this case, the mean of the system output is greater in production lines characterized by high task heterogeneity (Figure 2). This observed effect was explained in Shafer, Nembhard, and Uzumeri (2001), where is concluded that high levels of heterogeneity between workers result in a greater amount of total output.

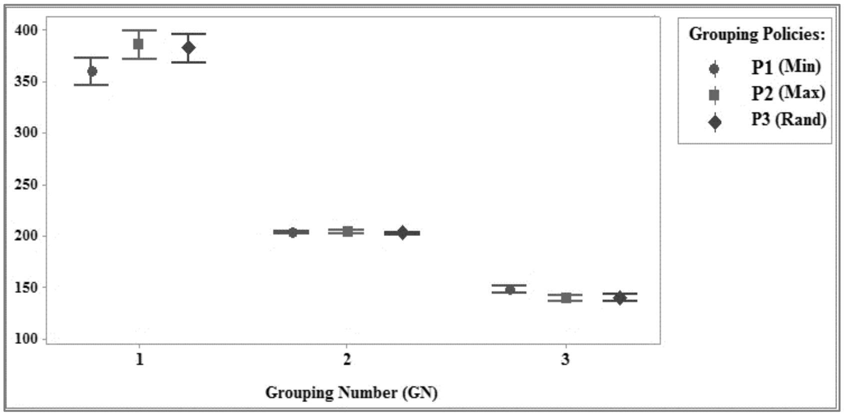

Figure 3: Main effects for the within-group variation analysis for the system composed of 3 workstations.

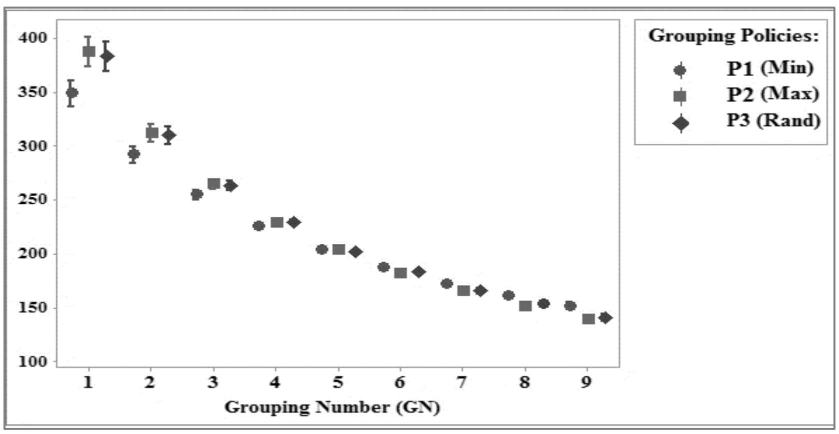

Figure 4: Main effects for the within-group variation analysis for the system composed of 9 workstations.

The third factor analyzed in this experiment is related to the dimensionality of the production system. In this factor, two organizational scenarios were analyzed, composed of three and nine workstations. The main effects plots related to this factor are shown in Figures 1-2 for serial and parallel production systems, respectively. In both cases, the size of the production line resulted significant for the system output (Table 5). In the case of the serial production line, a higher level of system output was obtained for the system composed of three workstations (Figure 1). In contrast, for the parallel configuration, the best system output was for the system composed of nine workstations (Figure 2). This behavior is explained by the additive effect, which determined the system output for the parallel production configuration.

When an analysis of the system was performed focused on the efficiency of the dimensionality of the system, the average units produced by workstations was greater in the case of the system composed by three workstations. In the case of the parallel system, the mean for the production line composed of three workstations was approximately 721 units. The rate of this system was approximately 240 units per workstation. For the case of nine workstations, the mean of the production line was approximately 2021 units, resulting in a rate of approximately 224 units per workstation. This results showed, that for the parallel production system composed of three workstations, on average each workstation is producing 16 more units than in the system composed by nine workstations. These results suggest that the system composed of three workstations was more efficient than the system composed of nine workstations as defined in this work.

5 CONCLUSIONS

This study addressed the grouping-assignment problem of heterogeneous workers on tasks of different complexities considering the workforce heterogeneity and knowledge transfer. Three essential research questions were investigated in this work: (1)Which heuristic policies perform best for the grouping-assignment of heterogeneous workers to tasks of different complexities when the production rate is modeled as a function of learning by doing and knowledge transfer?; (2)How does the dimensionality of the production system affect these results?; and (3)How does the consideration of knowledge transfer for the grouping-assignment of workers impact the system performance in different organizational configurations? A simulation experiment was executed to this end.

For the grouping-assignment process, three heuristic policies were examined in this work. The policy P1 was based on a variance minimization approach with respect to the knowledge transfer parameter θ and the task complexity as the prioritization rule. A policy P2 was defined based on a variance maximization approach with respect to the θ parameter. Finally, P3 was defined based on a random grouping-assignment approach. When the different heuristic policies were compared, the results showed that the policy based on a variance minimization approach (P1) performed best in the serial production configuration and a policy based on a variance maximization approach (P2) was favored for the parallel configuration. This means that (1) for serial production systems, grouping similar workers with respect to their capacity for learning by knowledge transfer results in a better performance than groups composed of more dissimilar workers when the system output is considered as a performance measure. In contrast, for the case of parallel systems, the formation of more heterogeneous groups is favored.

Additionally, the dimensionality and effect of the non-consideration of knowledge transfer were investigated. When different system sizes were examined, (2) the results showed that for both, serial and parallel production configurations, the heuristic policy which performed best for each case, presented a better performance in the system composed of 9 workstations. However, when the results were evaluated with respect to the average production per workstation, the system composed of 3 workstations showed a higher efficiency. Finally, when the non-consideration of the knowledge transfer for the grouping-assignment of workers was examined, (3) the results showed a significant improvement in the system performance when the workers were grouped based on the policy P1 for the serial production system, and P2 for the parallel production system, with respect to grouping workers randomly without considering their individual θ parameter. A limitation of the current study is that the model used in this work is not data driven. Future work will include the collection of additional data as a validation step.

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AUTHOR BIOGRAPHIES

Yaileen M. Méndez-Vázquez is a Ph.D. student of Industrial Engineering at Oregon State University. Her research interests include experimental design, simulation-optimization and the application of human learning simulation to workforce planning. 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. Dr. David Nembhard's research focuses on topics including workforce engineering, learning and forgetting, human performance, and transportation of hazardous materials. His email is david.nembhard@oregonstate.edu.