A statistical modeling approach for work design

Cintia PEREIRA[1], Daniela SCHNEIDER[1], Elenara MISSEL[1], Elisabeth THOMÉ[1], Flávio FOGLIATTO[2], Guilherme TORTORELLA[3], Michel ANZANELLO[2]

BACKGROUND

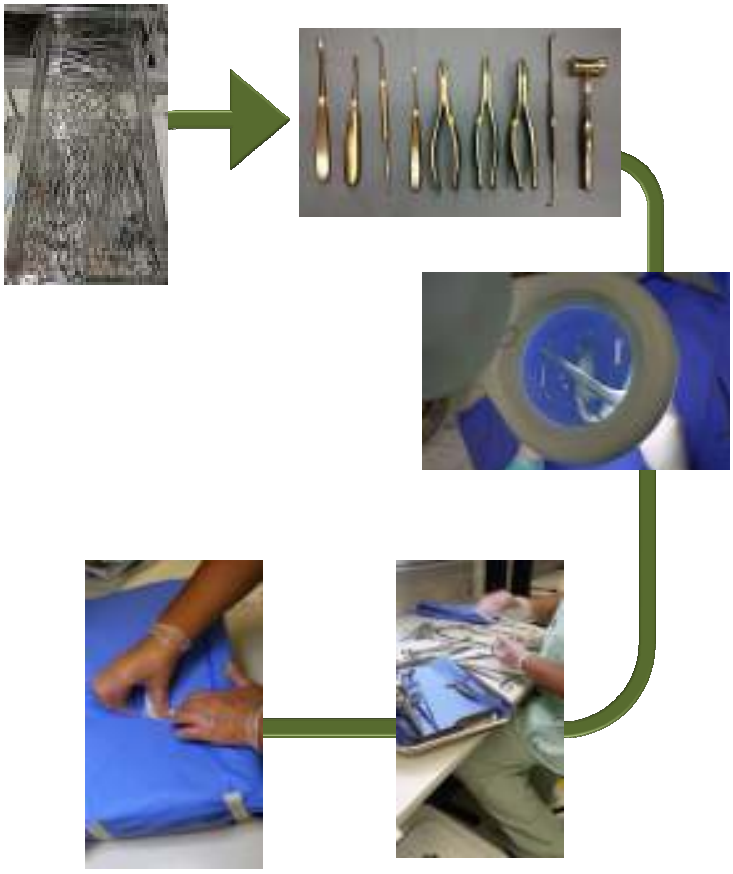
Assembly lines are extensively used in production systems to increase efficiency and productivity, reducing inherent manufacturing costs. However, if manual assembly operations are not properly designed the result may be task overload, with workers exposed to excessive physical work, insufficient rest, inadequate work conditions, monotony, and poor social relationship. Planning workers' processing times is a key factor in work design. In the healthcare industry the first time studies date 1914, when Frank Gilbreth proposed the application of motion study techniques to assess inefficiencies in healthcare services. More recently, an increase in the adoption of time and motion studies has been observed in healthcare and life sciences (HENDRICH, SKIERCZYNSKI, BOGAERT, 2008; WERF, VERSTRAETE, PAUWELS, 2009). A complicating factor typical to time studies in healthcare is variety. Tim! e data acquisition tends to be particularly tiresome due to the excessive number of tasks to be considered. However, time data are fundamental for proper capacity planning.

OBJECTIVES

To use of design of experiments to optimize time data collection in high variety sterilization departments, and regression analysis to model results and estimate the completion time of tasks not directly sampled in the time study.

PROPOSED METHOD

Our propositions are illustrated through a case study conducted in a sterilization department (SD) of a large University hospital. SDs are high variety production systems, characterized by the intensive use of manual labor; therefore, time studies are key in their capacity planning. In our case study, we focused on the assembly of surgical trays of instruments.



Cluster 1	Small (5-41)	Medium (42-65)	Large (66-135)
Vascular (100)		Tr. 4 (45; 310) / Tr. 5 (45; 431)	Tr. 7 (135; 1109) / Tr. 8 (123; 1085)
General Video (80)	Tr. 1 (31; 485)		
Cardiac surgery (90)		Tr. 6 (53; 422)	Tr. 9 (121; 685)
General Robotics (90)	Tr. 2 (10; 960)		
Dig Sys Rob (100)	Tr. 3 (18; 348)		
Cluster 2	Small (5-41)	Medium (42-65)	Large (66-135)
Neurosurgery (100)	Tr. 10 (31; 455)		Tr. 16 (65; 438)
Prostheses et al. (100)		Tr. 13 (65; 1647)	Tr. 17 (184; 1890)
Urology (80)	Tr. 11 (22; 392)	Tr. 14 (47; 680)	
Otorhino (70)		Tr. 15 (35; 385)	Tr. 18 (121; 950)
Gynecology Rob (90)	Tr. 12 (11; 887)		
Urology Rob (70)			
Cluster 3	Small (1-20)	Medium (21-46)	Large (47-125)
Thoracic (64)	Tr. 19 (2; 297)		Tr. 25 (135; 1200)
Oral and Maxilo (64)		Tr. 22 (49; 900)	Tr. 26 (92; 1004)
Orthopedics (48)	Tr. 20 (17; 401)	Tr. 23 (39; 755)	Tr. 27 (51; 884)
Proctology (48)	Tr. 21 (8; 206)		
Gynecology Video (56)		Tr. 24 (27; 600)	
Cluster 4	Small (3-41)	Medium (42-64)	Large (65-112)
Plastic (35)	Tr. 28 (10; 173)		Tr. 34 (84; 404)
Mastology (28)		Tr. 31 (65; 535)	
Pediatrics (35)	Tr. 29 (27; 258)	Tr. 32 (43; 601)	Tr. 35 (63; 600)
Gynecology (35)	Tr. 30 (10; 325)		
General (35)		Tr. 33 (58; 266)	Tr. 36 (110; 630)

RESULTS

The SD under analysis assembled 520 different types of surgical trays supplying 21 specialties in the surgery unit. Using DOE to optimize time data acquisition 36 surgical trays were sampled, i.e. less than 10% of the total.

CONCLUSIONS

Using data gathered in the experiment we obtained a regression model that predicted time to completion of trays that were not sampled with a maximum 18% margin of error. In validation trials that margin was never larger than 8%.