Analyzing Resource Behavior to Aid Task Assignment in Service Systems

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Abstract. Service organizations increasingly depend on the operational efficiency of human resources for effective service delivery. Hence, designing work assignment policies that improve efficiency of resources is important. This paper explores the role that data (specifically service execution histories) can play in identifying optimal policies for allocating service tasks to service workers. Using data from the telecommunications domain, we investigate the impact of assigning similar and distinct tasks within the temporal frames of a day, across days and a week. We find that similar work, when done within a day, significantly improves the efficiency of workers. However, workers working on distinct tasks across days also have higher efficiency. We build a simulation model of the service system under study, to gain insights into the dispatch policy considering similarity and variety of tasks assigned. Our work demonstrates use of data to generate critical insights on resource behavior and efficiencies, that can further aid in improving task assignment to resources.

Keywords: Resource assignment · Task similarity · Task variety · Simulation model

1 Introduction

A *service system* as defined by Sphorer [9] is an important unit of analysis in support of understanding the operations of an organization. A service system comprises of resources (that include people, organizations, shared information, technology) and their interactions that are driven by a process to create a suitable outcome to the customer. Arguably, the most critical resources in a service system are human resources. Without loss of generality, we shall refer to these as Service Workers (SW). Unlike machines or equipment, the behavior and efficiency of service workers is highly variable, and contingent on factors such as the experience gained from repeated execution of similar tasks (and potentially negatively impacted by the well-known psychological pitfalls that accrue from a lack of variety). Understanding resource behavior is critical as the overall efficiency of the service system or the service organization largely depends on the resources.

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Several large service organizations provide services that involve procedural and repetitive tasks i.e. tasks that do not require creativity and innovation. Service workers are commonly assigned or reassigned tasks based on a variety of criteria including experience, skills, their availability and sometimes other, often arbitrary, measures. It is important to note that in an environment that emphasizes the need for cost efficiencies, these traditional measures of suitability (of a service worker to perform a particular task) may not be sufficient and in some cases relevant. Instead, it is critical to identify work design and allocation policies that can improve the efficiency of human workers. In the context of work design and assignment, there are studies indicating distinct approaches: (a) assign similar work to a service worker where rhythmic and repeatable work will result in improved efficiency [13], (b) assign different tasks to provide variety of work to the service workers and improve their motivation and reduce boredom [10]. (c) balance both similar and variety of tasks assignment to the worker [10]. There are limited studies on evaluating the influence of work design and efficiency and using it to aid task assignment, especially in domain where workers are multi-skilled and not every one in a team can perform the task. For example, how does short term experience of a worker influence efficiency? Does variety of work have an impact or influence on day to day work efficiency? Does multi-skilling provide benefits of variety to a service worker? We aim to address some of these questions through this work.

In this paper, we study the data from a large service system, from the telecommunications domain, and evaluate the efficiency of service workers with respect to work done in a short time frame such as a single day, across days and weeks. That is, we study the impact of short-term experience on the efficiency of workers. Further, we describe a heuristic approach for an improvement in productivity of a worker, based on findings and make targeted assignment of workers to tasks. The approach considers similar and distinct work done by workers in immediate past to make future assignment. Evaluation of a heuristic assignment policy is performed using discrete event simulation that mimics the operations of the service system under study. This paper considers a common type of service system, where efficiency of service workers directly contributes to organizational productivity. Ultimately, our work serves to highlight the utility of performing such analysis to generate domain-specific, or organization-specific insights.

The outline of this paper is as follows: We discuss related work in Sect. 2. Next, we define key concepts, present our hypothesis and discuss our data collection i.e. the data used for our analysis, in Sect. 3. Section 4, presents our data analysis and model developed to support our hypothesis. In Sect. 5, we build a simulation model to evaluate the improvements possible when assignment is done considering the work done by resources prior to the task under consideration. We discuss validity of our results in Sect. 6. Section 7 concludes the paper.

2 Related Work

In this section, we outline the background of our study in the light of related work. We present the research trends in two specific areas related to our study.

2.1 Modeling Service Systems

A resource model as defined by Ramaswamy et al. [17], forms a key element in building a formal service delivery model. Resources having capabilities required by tasks of service delivery process, are assigned to the process, to enable its completion. Resources in service systems are humans, referred to as Service Workers (SW). Service system models define attributes of service workers, such as availability by considering shifts roasters and capability by defining a skill vector. A Work or Service Request (SR) arriving in the service system is defined by considering complexity, severity (or importance) and the minimum capability required to complete the work. Dispatching policies [2], with considerations to the tardiness, lateness and utilization of the resources have been evaluated with respect to various service system workloads, that assign a SR to one or more service workers. In their work, Diao et al. [6] present the first detailed model of a complex delivery system. A model for an optimal labor cost given complex constraints of resource availability, capability and service level is defined. In one of the recent studies on service systems [1], the authors discuss how teams can be formed in accordance with one of the following service delivery models: (a) Customer focused (b) Business Function focused and (c) Technology-focused. Here authors hint, that the choice of the delivery model organization should be based on multiple factors, one of which is the expertise or skill of knowledge workers. Further, study on organizing service systems with teams having multiple skills has been evaluated and compared to social compute units [5,18]. In these studies, the operational efficiency of resources with specific capability, is considered to be homogeneous. Our work, extends from existing service system studies, and defines a dispatching model based on the insights gathered from the data, by defining allocation policies influencing resource efficiency.

2.2 Resource Behavior Analysis

Behavior of resources, when executing processes has attracted significant research interest in the recent years. In [22], common pitfalls associated with building simulation models, has been highlighted, that includes incorrect modeling of human resources. The authors emphasize incorrect representation or modeling of human resources as the cause of simulation models providing misleading outcome measures. Outcome measures refer to the average utilization of resources, average throughput or number of requests completed periodically, service quality that includes completing work within a specified target time. A process mining framework that can be used to detect outliers in resource behavior indicators (RBI) has been proposed in [16]. RBIs include metrics related to resource utilization, resource skills and productivity. The framework helps in time series analysis of indicators for each resource. In [19], the authors present an approach that uses historical data and illustrate variance in operational productivity of workers, for requests with different priorities and complexities. Variances in efficiency of workers are used to define policies for dispatching and optimally staff teams. Organizational behavior research to improve work design indicates two distinct strategies of specialization and variety. In one of the recent studies by Staats et al. [20], the authors suggest that specialization or similar work during a single day improves the productivity of the worker while variety of tasks across days, helps in retaining the worker within the organization. The study has been carried out for a Japanese Bank where a large part of the process is automated and human resources involved in executing manual tasks of the process do not require any specialized skill or training. Narayanan et al. [10] analyze the degree to which task specialization enhances learning, and show that excessive exposure to task variety is an impediment to learning. Learning effects have been observed for repetitive tasks in manual, cognitive and knowledge-based work [12]. In [15], the authors present the idea that similar case instances in a row can be processed faster than randomly distributed case instances. Case instances that possess similar attributes are grouped together and distributed to resources at runtime. Depreciation or forgetting models and its effects has been studied by a few assignment models [11]. Learning and forgetting models help in identifying the assignment policies prior to workers achieving steady state of productivity. Hence, as indicated in much of the work done in the past, resource behavior has an important bearing on the efficiency and quality of a business process.

In this work, we seek to study how the experience gained in a shorter temporal frames, impacts worker efficiency. The study is conducted on a service system, in the telecommunications domain, requiring specialized skills. We further use the insights gained from the study to aid task assignment (or dispatch policy), and evaluate outcome measures of the service system.

3 Background

We now outline the context of our study by presenting the concepts of service system used in this study.

3.1 Service System

Work arrives into the system when customers request for a service. Work is defined by a work type and is further characterized by a set of capabilities required to complete the work. Resource(s) having the capabilities are assigned to the work for completing it. There are several dispatching policies that are used to assign work to a resource. In certain service systems, the task or work may require more that one resource, and is handed over to multiple resources to complete it. In this study we limit ourselves to scenarios where a single resource completes the work, as the service system that we study consists of tasks that requires a single SW to complete the work. We define key concepts underpinning the service system below:

Work Request or Task. Work requests constitute inputs to the service system and are handled by service workers. Typically, a work request (WR) is characterized by a work type. In this paper, we use task, request and work request interchangeably.

Skills. A finite set of skills pertaining to the domain defined by S.

WorkType. Work type categorizes a work request. There are a finite set of Work Types WT. There is one to many relation of work type to skills required for the work type defined by $w : WT \mapsto S$.

Service Workers. Service Workers are the human resources in the service system, who work on Work Requests. There a finite set of service workers SW. A one to many relation of service worker to skills possessed by the worker is defined by $s : SW \mapsto S$.

Service Time. Service time refers to the time a service worker spends to complete the work request. Hence, it is the time between the work request being assigned to the worker, to the time the service worker completes the request.

Work Arrivals. The arrival pattern of service requests is captured for finite set of time intervals T (e.g. hours of a week). That is, the arrival rate distribution is estimated for each of the time intervals in T, where the arrival rate is assumed to follow a stationary Poisson arrival process within these time intervals (one hour time periods) [2,7].

Dispatching or Task Assignment. The task assignment is done by assigning a work request to a service worker with the necessary skills such that $w \cap s \neq \varnothing$. Hence, a SW with any one of the skills required for the work type of the work request can be assigned the work request.

An important consideration in assigning task to service workers is their availability and suitability. To evaluate the tasks that service workers work on and their operational efficiency, we introduce the following hypotheses that guide our investigations:

HYPOTHESIS 1: Doing similar work within a day has a significant influence on productivity of a service worker and its influence lasts for a day.

Consistent with the previous research [20], doing similar work helps worker perform certain steps in the process faster, that improves operational efficiency or reduces service time. We further, evaluate the influence of doing similar work in immediate past such as previous day and week to determine the temporal frame of influence.

HYPOTHESIS 2: Working on work requests of different work types, i.e. doing a variety of work has an influence the operational efficiency of a service worker.

Studies indicate that, variety of work has an influence on employee turnover. Task variety lowers levels of boredom [23] and increases job satisfaction [8,20].

HYPOTHESIS 3: Multi-skilled service workers focus on a limited number of work types. The benefit of training on multiple skills diminishes with workers focusing on a smaller percentage of work types.

Multi-skilling has been recognized as a tool for increasing production flexibility [14]. Studies in the past indicate multi-skilling through cross-training in a manufacturing set up, to be beneficial but find greatest benefit when cross-training is minimal [4,14].

3.2 Setting and Data Collection

The setting for our analysis is a large telecommunications service provider organization. The organization provides services for fixed line telephone, mobile telephone and broadband services. A process aware information system (PAIS) is used, where customers using service of the organization report problems related to the services e.g. internet speed, modem failures, phone lines not functioning etc. Depending on the problem, a work request is created with a specific work type. Technicians from the service provider organization are assigned to work on these work requests and resolve them. Each technician, goes to the customer site and resolves the issue. A large percentage of problems or requests are handled by a single technician ($\sim$94 %). Once a technician completes the task, a new task is assigned. A technician spends time in traveling from one customer location to another location. We do not consider the travel time in our study. The service time is computed as the time spent between a technician reaching the customer's premises and time of completion of the request. Each technician has one or more domain skills that enables to address problems of specific type: problems related to cable management, plain telephone service, digital subscriber line etc.

The PAIS helps capture the time an issue was raised by the customer, the work type, the time at which the technician reached the customer site and the time when the technician solved the problem. A period of 3 months is analyzed with more than 89000 work requests served by 490 technicians. There are close to 30 work types that have less than 100 work requests. We drop these work requests from our study leaving us with 78,350 work requests served by 480 technicians. The distribution of natural logarithm of service time in minutes has a mean of 4.28 and standard deviation of 0.768 is shown in Fig. 1(a). Resources complete between 1 to 8 tasks in a day depicted in Fig. 1(b).

4 Data Analysis

This sections presents the models developed to support the hypothesis presented in Sect. 3.

4.1 Performance Improvement Doing Similar Work

For testing our hypothesis 1, we use linear regression models to understand the relationship and influence of work done by service workers within a day, previous day and week on the service times. The service time is the dependent variable in the model.We compute the following independent variables:

- Number of Prior Similar Tasks (SimilarTasks): The number of work requests having the same work type as the current task, completed before the task in the same day.
- Number of Prior Dissimilar Tasks (DissimilarTasks): The number of work requests having different work type as the current task, completed before the task in the same day.

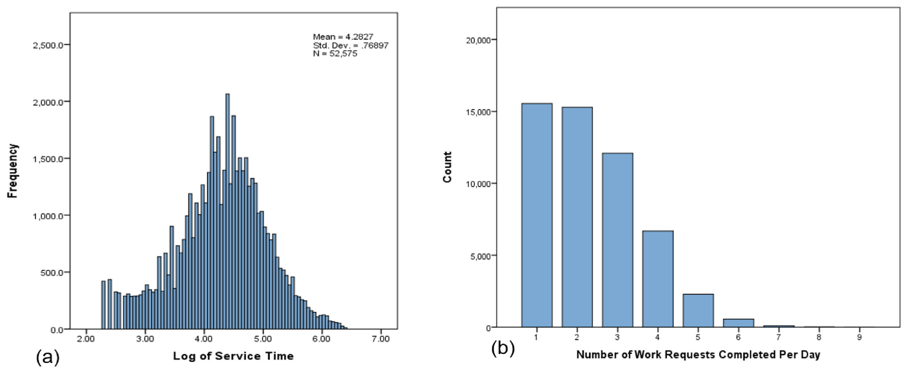

Fig. 1. (a) Distribution of log of service time (b) Histogram of work completed by resources per day

- Number of Similar Tasks Previous Day (PreviousDaySimilarTasks): The number of work requests having the same work type as the current task, completed on the previous day.
- Number of Similar Tasks in Week (WeekSimilarTasks): The number of work requests having the same work type, completed during the week.

These independent variables will help understand the temporal impact of working on similar tasks and the impact of working on different tasks in a single day.

We use multiple linear regression to understand the influence of independent variables on the dependent variable. We report the estimates of the coefficients of the independent variables along with their standard errors. The magnitude and the sign of the coefficients indicate the degree and directionality of influence of the corresponding independent variable on the dependent variable. The t value is the ratio of each coefficient to its standard error. Using this t value and the Student's t-distribution, the p value is calculated. If the p value is less than the significance level (usually taken to be 5 % or 1 %.), the corresponding result is statistically significant. DF denotes the degrees of freedom. F is the Fisher F-statistic - is the test statistic for testing the statistical significance of the model. R^2 is the coefficient of determination - the ratio of the regression sum of squares to the total sum of squares, indicating the goodness of fit of the regression model. To compensate for over-fitting a model, adjusted R^2 is used that adjusts the R^2 value for the number of variables in the model. The objective of building the model, as indicated earlier, is to understand the influence of independent variables on the dependent variable.

We build a simple model, with the log(service time) as the dependent variable and all the other independent variables indicating similar work and dissimilar work done by the technician prior to doing a particular task. We also control for the total work done by each technician every week as technicians or workers can have different volumes of tasks assigned. This is done by adding the total work done by each technician every week (TotalWorkInWeek) as an additional variable into the regression model. The output of the model is shown in Table 1. This model shows that doing similar tasks in a day improves the service time. For example a worker doing a similar task twice in a day will have the service time of the second task reduced by a factor of 0.9 ($e^{-1*0.097} = 0.907$). Doing dissimilar tasks in the same day prior to the current tasks does improve the service time, but is lower than of doing similar tasks in the day. The influence of the tasks done in the previous day, on the service time is statistically insignificant as shown in the model. Hence, work done on the previous day, does not have any significant influence on the service time of the technician. Table 1 presents standardized estimate, that refers to how many standard deviations a dependent variable changes, per standard deviation increase in the independent variable. Standardized estimates help evaluate independent variables, that have a greater effect on the dependent variable. Doing similar tasks in the week improves service time, accounting for experience gained through the week. From the model, influence of doing similar tasks in a day and week has a large effect on the efficiency of the service worker. Therefore, this provides support for hypothesis 1.

Table 1. Multiple linear regression model showing service time based on similar tasks done in a day, dissimilar tasks done in a day, similar tasks done previous day and similar tasks done in a week.

	Estimate	Std. Estimate	Std. Err	t value	p-value
Intercept	4.282		0.013	319.6	<0.0001
SimilarTasks	−0.097	−0.073	0.005	−19.86	<0.0001
DissimilarTasks	−0.046	−0.040	0.004	−11.10	<0.0001
PreviousDaySimilarTasks	0.004	0.003	0.005	0.764	0.445
WeekSimilarTasks	−0.023	−0.098	0.001	−22.25	<0.0001
TotalWorkInWeek	−0.01	−0.051	0.001	−19.93	<0.0001
	DF = 78349	F = 1038.21	Adjusted R^2 = 0.062		

4.2 Efficiency Improvement with Variety in Work

To study the impact of variety in the work done by service workers (hypothesis 2), we compute two independent variables:

- WorkerCapability is the number of work types a worker is capable of working on based on the skills possessed by the worker and skills required by the work type.
- WorkVarieyIndex is the ratio of the number of work types a service worker works on (on the job), and the WorkCapability. Valid values of WorkVarietyIndex would lie between [0,1]. A higher WorkVarietyIndex is indicative of a worker working on different work types, and hence, higher variety.

WorkVarietyIndex is incorporated into the existing model (of Table 1). We control for WorkerCapability because some workers may be trained on too few, or too many skills and hence, have very low or high WorkCapability respectively. The model with WorkVarietyIndex is shown in Table 2. Service workers with higher WorkVarietyIndex have lower service time indicated by its negative coefficient. Hence, it supports our hypothesis 2 of work variety improving the operational efficiency of service worker.

Table 2. Multiple linear regression model showing service time based on similar tasks done in a day, dissimilar tasks done in a day, similar tasks done previous day and similar tasks done in a week and WorkVarietyIndex.

	Estimate	Std. Estimate	Std. Err	t value	p-value
Intercept	4.180		0.027	215.77	<0.0001
SimilarTasks	−0.098	−0.073	0.005	−18.196	<0.0001
DissimilarTasks	−0.044	−0.040	0.004	−13.895	<0.0001
PreviousDaySimilarTasks	0.002	0.001	0.003	0.419	0.675
WeekSimilarTasks	−0.005	−0.011	0.001	−3.847	<0.0001
TotalWorkInWeek	−0.001	−0.005	0.001	1.93	0.153
WorkVarietyIndex	−0.125	−0.051	0.014	−9.681	<0.0001
WorkCapability	0.001	0.092	0.000	36.976	<0.0001
	DF = 73940	F = 1266.386	Adjusted R^2 = 0.107		

4.3 Influence of Multi-skilling on Variety in Work

Multi-skilling allows workers to be more flexible addressing changes in demand, absenteeism and work assignment. We created a simple model to examine the relationship between variety in the work done by service workers, during the period of study (WorkTypes WorkedOn) and the variety in work a service worker is capable of working on by virtue of skills possessed (WorkType Capable). The result of the model is presented in Table 3. We use linear regression model without an intercept. The model shows that, workers are utilized on 21.7 % of the work types they are capable of. This could be, due to workers possessing a large number of obsolete skills that may not have any demand. However, based on the model and results, hypothesis 3 of workers focusing on a limited number of work types is supported by Table 3.

4.4 Dispatching Considering Resource Behavior

Service time influences the number of requests completed per day or week by a service worker (throughput) and the time a resource is busy servicing the requests (utilization). Our model observations can be used to improve the dispatching rules or policies when assigning tasks to service workers. Algorithm 1 formally describes the policy. Initially, the minimum permissible queue length i.e. queueLenThreshold, is set to zero. queueLenThreshold is the number of requests that can be pending with the service worker. The dispatching policy checks for service workers with minimum permissible queue length and possessing the required skills. Among them, it finds a service worker, who has completed a minimum of 1 work request similar to the work type of the WR to be assigned. This is to account for assigning the work that is similar to previous completed

Table 3. Model predicting WorkTypes workedOn using WorkType Capable.

	Estimate	Std. Error	t value	p-value
WorkType Capable	0.217	0.00	911.7	<0.0001
	DF = 485	F = 882.647	Adjusted R^2 = 0.646	

work. If there are no service workers available, then the policy looks for service workers having a queue length of 1 and 2 by increasing the minimum permissible queue length, until the MaxQThreshold is reached. If it does not find any service worker, then the service worker with the least queue length is chosen. In the following sections, we refer to this policy as SimilarWorkDispatch policy. In the next section, we compare SimilarWorkDispatch policy to the policy of assigning tasks to a worker with suitable skills and the lowest queue length. We refer to the dispatching policy of assigning work to a SW with the required skill and lowest queue of pending requests as MininimumQueueDispatch policy.

```
Input: WR, SWList
Output: SW_id
id = φ;
queueLenThreshold = 0 ;
MaxQThreshold = 3 ;
while id = ∅ OR queueLenThreshold < MaxQThreshold do
    maxPreviousSimilarWR=0;
    foreach w_i ∈ SWList do
        if w_i.QueueLength == queueLenThreshold then
            // get number of completed requests matching WR workType ;
            wSimilarCount = getCompletedSimilarWorkInDay(WR);
            if wSimilarCount > maxPreviousSimilarWR then
                id = w_i.id ;
                maxPreviousSimilarWR = wSimilarCount ;
            end
        end
    end
    if id == ∅ then
        queueLenThreshold = queueLenThreshold + 1;
    else
        break ;
    end
end
if id == ∅ then
    id = getWorkerWithLeastQueueLength;
end
```

Algorithm 1. Work Similarity based Dispatching Policy considering previous similar work done by service workers

5 Simulation Based Experimentation

We describe the simulation set up that mimics the service system being evaluated. The simulation model enables us to compare overall performance of the service system using a dispatching policy that considers resource behavior, as described in Sect. 4.4 - SimilarWorkDispatch policy, and MimimalQueueDispatch policy. Each Work Request that comes into the system is assigned to a suitable service worker based on the dispatching policy. For the purpose of simulation, the following parameters are set.

- Work Arrivals: A finite set of time intervals for arriving work, denoted by T, containing one element for each hour of week. Hence, $|T| = 168$.
- Work Type: A finite set of WorkTypes are generated and each work request is associated with a work type when it is created.
- Worker Queue Length: Each service worker has a queue. The number of requests in the queue determines the load on the worker.
- Service Time: The service time of the worker used in the simulation model is based on the service system under study. For each work request, the number of prior similar work types completed by the service worker, within the day, is computed. The mean and the standard deviation of service time, for a specific number of prior similar tasks is computed. Figure 2 shows the plot of means of log service time varying with the number of similar tasks done within a day. In the simulation experiments, we compute the service time for each worker based on the (μ_s, σ_s) with s indicating the number of similar tasks done by the worker in the day.
- WorkVarietyIndex: The WorkVarietyIndex for simulation experiments uses a normal distribution with a mean, $\mu = 0.27$ and a standard deviation, $\sigma = 0.07$. Figure 2 shows the box plot of WorkVarietyIndex of the system under study. Each SW is assigned a WorkVarietyIndex based on the normal distribution with the mean and sigma values of the SS under study. The service time of a technician with higher WorkVarietyIndex is lowered by factor $(e^{-0.125*WorkVarietyIndex})$. The coefficient -0.125 is taken from the regression model. WorkVarietyIndex is associated to each SW.

We build the service system model using AnyLogic simulation software [3,21] which supports discrete event simulation technique. We simulate up to 40 weeks of simulation runs. Measurements are taken at end of each week. No measurements are recorded during the warm up period of first four weeks. For our experiments, we consider request arrivals follow a Poisson model where the inter-arrival times follow an exponential distribution. In steady state the parameters that are measured include:

- Throughput or the number of work requests completed per week.
- Resource utilization: captures ratio of busy-time of a resource to the total time of the simulation run.

The simulation model is evaluated with the work arrivals derived from data. For the purpose of simulation, a smaller subset of the real-life data is used.

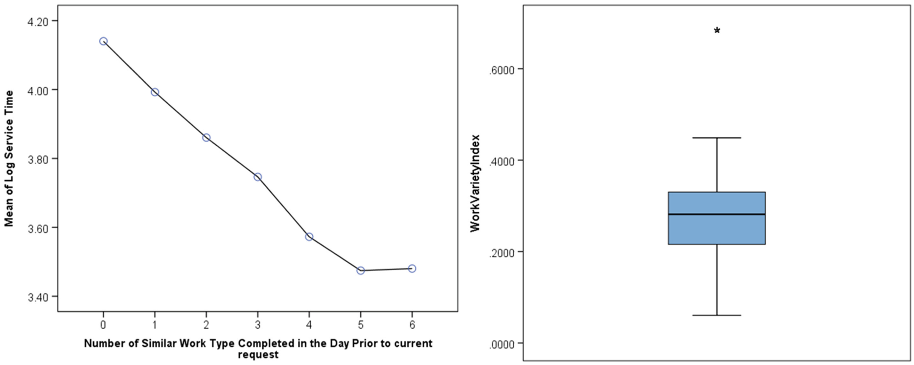

Fig. 2. Mean of Log Service Time with Similar Work done in the day, Box plot of WorkVarietyIndex

Each work is associated to one of the 15 work types similar to that of the service system under study. One hundred service workers are instantiated in the model. Each service worker is multi-skilled and is initialized with a specific WorkVarietyIndex. The results of the simulation experiments are presented in Fig. 3. Results compare two dispatching policies - MinimumQueueDispatch, SimilarWorkDispatch. The SimilarWorkDispatch policy is run for different value of MaxQThreshold values. As indicated in Fig. 3, SimilarWorkDispatch policy provides higher throughput when the MaxQThreshold = 2. At higher values of MaxQThreshold, the algorithm starts dispatching to workers with higher queue length. The throughput reduces as the requests wait in the queue of the service workers. Hence, for higher MaxQThereshold values, the gains from improved service time, by doing similar work, is offset by the wait time in the queue of the service worker. An additional simulation is run where workers do not have any variety in their work or the. WorkVarietyIndex of service workers is set to 0 - SimilarWorkDispatchNoVariety. The observation is made to validate the improvement achieved by workers having variety in their tasks.

Figure 3 also compares the average resource utilization between these distinct dispatching policies. As the MaxQThreshold for SmartWorkDispatch policy increases, there are a few resources assigned the task (resources who have done similar work), while other resources remain free. Hence, the average resource utilization reduces. Hence, the SmartWorkDispatch policy is sensitive to the MaxQThreshold which should be set based on the evaluation of historical data for a service system.

Applying Insights from the study: The insights obtained from the simulation runs can be applied in practice to improve the efficiency of the service system. Important considerations that emerge from the experiment are: (i) Dispatching similar work provides substantial improvement in the performance of the service system, (ii) The gains due to the dispatching similar work policy should be evaluated based on the reduction in service time by doing similar work and the

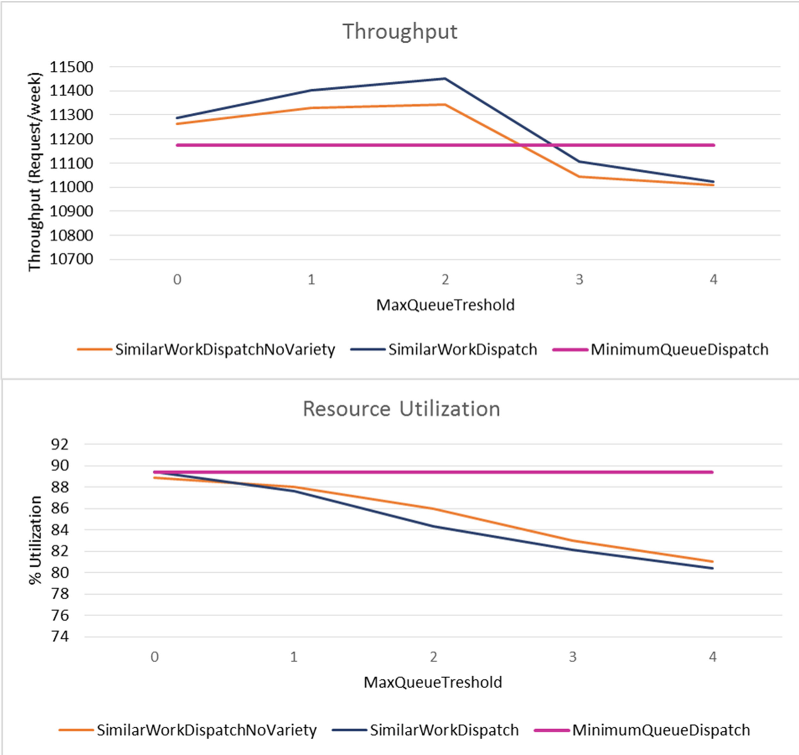

Fig. 3. Throughput and Resouce Utilization comparing (a) Similar Work based dispatch (b) Worker with minimum Queue length

wait time in the queue of busy service workers. (iii) As work variety improves the performance of the service system, variety in can be balanced by dispatching different work types across days and similar work within a single day.

6 Threats to Validity

There are some potential threats to validity for this work. It is extremely hard to predict the behavior of human resources working on tasks requiring specialized skills. The adjusted R^2 of the regression models were small, indicating that these effects highlight a small amount of the wide variance in the service time of the workers. However, our results are in line with some of the work done in the past [20,23], in the broader context of organizational behavior and work design and do provide insights on the influence of similar and variety of work done on the service times of workers. In this system under study, data related to quality of work done was not captured. Hence service time has been viewed as an imperfect proxy measure of quality.

Further, we have studied a single, but large service system in this work. While, the work requests handled by the workers is repetitive, they are not done in large volumes. The service levels for the requests are relaxed and the workers do not have any specific targets to finish in time. While insights can be drawn from our study, we do not claim that these results can be generalized in all instances. These results serve as the basis of using data driven approach for evaluating understanding resource behaviors in similar contexts and use them to improve task assignment.

7 Conclusion and Future Work

In this paper we studied the data from a large telecommunication service provider system. The impact of assigning similar and dissimilar tasks to a worker in a temporal frame of within a day, across days and a week was analyzed. From our results, we observe efficiency gains by a worker is significant when doing similar tasks in a day. Further, doing variety of work across days also improves efficiency. A simulation model was used to evaluate benefits of establishing a dispatching policy for task assignment. Through this work, we demonstrate, the value of such analysis in specific organizational contexts. In future, we would evaluate and analyze resource efficiency in other domains such are IT service management requiring specialized skills for completing tasks.

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