

# Agent-Based Service Analytics

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## INTRODUCTION

Service sector forms a growing portion of world economy; Archarya (2006) estimated that service economy accounts around 50% and 70% of the total value adds in the developing and developed countries, respectively. Wolf (2006) reported that service industries, including social and personal services as well as business services, are performing poorly in terms of productivity growth. In overall sectorial comparison, the service sector still seems to lag behind manufacturing. There were various thoughts dedicated to improving service productivity. Sherman and Zhu (2006) proposed a data envelopment analysis (DEA) method to benchmark service performance. Li (2008a) compared between a manufacturing process and a service process, and suggested opportunities of improving service productivity across service cycle via software technology.

In the service business, a recurring issue is how to optimize demand and supply to achieve business benefits for a service enterprise. Traditionally, academic researchers and industrial practitioners resorted to manufacturing production planning techniques such as System Dynamics (SD) and Discrete Event Simulation (DES) to help solve service production planning problems. Antoniol, Cimitile, Di Lucca and Di Penta (2004) used queuing simulation to access staffing needs for a software maintenance project. Liu and Wang (2007) applied constraint programming as the searching algorithm to optimize resource assignment problems of linear construction projects. Li and He (2008b) devised new local search heuristics to optimize lead time and resource utilization for utility service enterprise; previously the focus of

resource allocation was more on cost saving than on customer experience.

Manufacturing production planning methods use statistic models to approximate demand and supply, and match demand with supply to identify and fix gaps. In a geographically-distributed service operation, resource planners tend to group demand and supply into regional buckets based on geographical and skill distributions of the business. They then apply production planning methods to optimizing each service operation bucket. During the matching, individuals in the demand and resource are often treated indifferently such that a uniform mapping between demand and supply can be arranged. Examples of matching are the required number of programmers for software work packages, civil engineers for construction activities and field technicians for telecom service tasks.

In industrial practice, however, traditional manufacturing production planning methods have constantly met fierce challenges from service planning and operation community. The reason is that statistical approaches often try to abstract real-world problems so that standard mathematical models can be used to represent the problems. In doing so, original problems are often over-simplified perhaps even distorted and a large amount of key information gets lost. Take field service for example, every field technician has unique skills, geography and productivity; the matching between a task and a technician is not a simple linear mapping but determined by scheduling rules, location and type of next task, current location and skill of technician, travel time from current location to the next, onsite time spent by the technician for the task, etc. Taking a simple average and variance from the bucket won't reveal a

technician's individual circumstance, performance and opportunity for optimization.

*Agent-Based Service Analytics (ABSA)* is a new analytical framework, coined by the author, to address the deficiency of manufacturing production planning methods when reused in the service domain. It is composed of a suite of techniques for the end-to-end analytical tasks such as service modeling, visualization, analysis, simulation and optimization. The key drive of this framework is to understand the behavior and optimization opportunity of individual agents in a service process, be it customer, employee or supplier, which are often the ultimate questions asked but cannot be answered by the service planners and operators. This is in contrast with optimization in a manufacturing process where the interest is in process activities and the aggregated number of identical entities flowing through each activity.

Having its origin in computer science, Agent-Based Simulation (ABS) had its early adoptions in science, sociology and economics. However, in Operational Research (OR), especially in the area of service management, the adoption of ABS has been slow. There are still considerable doubts and debates regarding what is ABS in OR, why and when should ABS be used, how should ABS be used for data-intensive industrial applications, how should a ABS project be properly managed, what new curriculum needs to be established in school to educate an industrial ABS analyst. In this chapter, the author tries to share his insight into these questions based on his vision on co-evolution of socio-economy and simulation paradigms as well as his hand-on experience in developing an ABSA framework that has been adopted by a large field service operation.

### TOWARDS AN AGENT-BASED SERVICE ANALYTICAL FRAMEWORK

Throughout the discussion, the author will use field service domain as a generic example. In this

scenario, a service task for a customer could arrive in real-time randomly, have individual requirement (geography, task type, target date & time, priority); a field service technician could have customized attendance schedule, personal home location, own skill set, individual productivity, and special travel condition. A work controller is responsible for allocating tasks to technicians based on certain rules so that the individual requirement of each task can be satisfied and any deviation from that requirement is considered as a total failure. As the service market evolves, new types of products and services could arrive that require constant re-skilling of the work force to cope with the demand changes, improve resource utilization and optimize service throughput.

*ABS for Service Sector and DES for Manufacturing Sector:* There are great confusion among academic researchers and industrial practitioners regarding what simulation methods to choose. In many aspects, a service process is quite different from a manufacturing process, as compared by Li (2008a). A service process often involves close interaction between a service customer and a service provider in which each interaction could be unique as human factors are involved; a manufacturing process, to the opposite, tries to decouple such interaction, so that production can be carried out in a well-controlled environment (factory) in which exceptions or variances are minimized. A service process often aims to make customers happy and buy more by satisfying their individual requirements whereas a manufacturing process is designed to deliver products in a uniform time and quality scale. A service process centers round labors; it needs to be very agile, flexible and adaptable to change to meet frequently changing new requirements. A manufacturing process centers round machine and equipment flows; it is relatively stable with less changes. In this context, the author believes ABS can be best used to model a service process to capture the great variance and agility across individual agent behaviors whereas DES should remain the ideal method to model a manufacturing process.

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