A SIMULATION-BASED DSS FOR FIELD SERVICE DELIVERY OPTIMIZATION

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ABSTRACT

This paper aims at presenting the preliminary results of a research targeted at developing a Decision Support System (DSS) for the Field Service Delivery System (FSDS) design. The paper is organized as follow: firstly, we illustrate what a FSDS is; secondly, we identify the variables to consider in order to design a FSDS and the relationships between them; thirdly, we describe how a DSS supporting the FSDS design should be developed; and finally, we show the result of of a pilot experiment in which a DSS has been developed and applied to a real case study.

Keywords: field service delivery system (FSDS), decision support system (DSS), discrete event simulation, after sales service

1. INTRODUCTION

This paper aims at describing a tool that can support the management of a Field Service Delivery System (FSDS), that is, the company's function devoted to deliver services – such as the product's installation and maintenance – directly at customer's site.

The rationale of the paper lies in the fact that, despite the increasing interest raised by field service in many industries and the large number of applications supporting the field service operations management, there is a lack in models/devices supporting the *design* of the FSDS (Visintin 2007).

A great deal of information is usually available in the Enterprise Information Systems, but generally there are not tools allowing service managers to fully and properly utilize these information, in order to understand the effects that different managerial policies can have on the overall system performance (Agnihotri and Karmarkar 1992).

Moreover, the FSDS design activity is a very complex task. It requires, in fact, to forecast *when* and *where* the service requests will arise, to figure out *what* skills and parts will be required in order to fulfill the service requests, and to decide *what* criteria should be followed to dispatch the technicians.

In addition to that, service managers are asked to achieve increasingly high performances, both in terms of customer satisfaction and costs.

Because of the complexity and the uncertainty characterizing the FSDS design there is a strong need of simulation-based tools supporting service managers. It is in fact tremendously expensive and time consuming, to modify the FSDS configuration ex-post.

The aim of this paper is thus to discuss how a Decision Support System (DSS) for designing the FSDS could be developed and to illustrate a first example of a DSS.

The paper is therefore organized as follows: firstly, we define and describe a generic field service delivery process; secondly, we identify all the variables that service managers should take into account to design the FSDS; thirdly, we assess if and where the information relevant to these variables can be found in the most common Enterprise Information Systems; fourthly, we describe how the discrete event simulation can be successfully used to create such a DSS; and finally, we show the result of a pilot experiment in which a DSS has been developed and applied to a real case study.

2. THE FIELD SERVICE DELIVERY SYSTEM

A FSDS is made of a set of technicians, each mastering a given set of skills and covering a given geographic area, that are remotely dispatched at the customers' sites to fix the customer's problems upon request (Blumberg 1991; Visintin 2007).

A typical field service process can be subdivided in three main activities:

1. help desk;
2. dispatching;
3. service delivery.

Figure 1 describes a typical field service delivery process.

The Help desk is the company interface with the customer, so it is devoted to receive the incoming service request, to identify the customer and to offer (when it is possible) a remote assistance, that is, to avoid the service delivery on-field.

If the call avoidance does not succeed, then comes the need of selecting and dispatching a field engineer to the customer (Agnihotri and Mishra 2004).

Finally, the selected technician gathers all the needed technical data and actually visits the customer.

In designing and managing this process, service managers need to take into account several variables

(Agnihotri and Chakravarty 2005), that we present in the next paragraph.

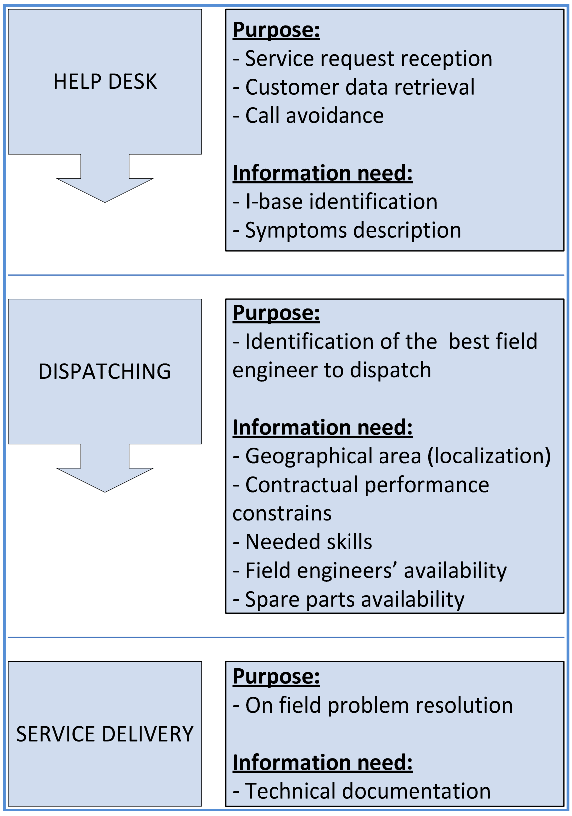

Figure 1: Field service delivery process description

3. FSDS DESIGN PROCESS VARIABLES

The design of a FSDS is a decision-making process characterized by several independent, dependent and control variables (Agnihotri, Narasimhan and Pirkul, 1990).

The control variables are those that managers can manipulate in order to obtain, in a given context, a desired outcome. They concern:

- the system *Capacity*, that is the overall number of technicians;
- the technicians' *Dispatching* policy, that is, how a service request is assigned to a field engineer;
- the technicians' *Scheduling* policy, that is, how the amount of service requests is planned to be served by the field engineers throughout the working day;
- the *Districting* policy, that is, the criteria to follow in order to assign each technician a territory;
- the *Cross-training* policy, that is, the criteria to follow in order to assign each technician a given set of skills (Agnihotri, Mishra and Simmons 2003; Upton 1994);
- the *Spare parts management* policy, that is, the way spare parts are stored, reordered and delivered to the customers.

The independent variables, are those out of the service manager's control, while the dependent variables, are functions of the independent and the control variables.

In Table 1 the aforementioned variables are described in detail, while Figure 2 shows the delivery system design process.

As we see, the independent variables represent the *input* for such a process, because they identify the context in which managers have to work and that they cannot control. The values of the independent variables are totally known before taking any system designing decision.

The control variables, instead, represent – to some extent – the *output* of the decision making itself. They are, in fact, the aspects that managers have to decide about, in order to design a FSDS. We can therefore say that the values of the control variables are the results of the decision making process.

Finally, the dependent variables are those measuring the *outcome* and thus the effect of the decision taken by the service manager. We can identify them with the actual system's operational and financial performances (Agnihotri 1989).

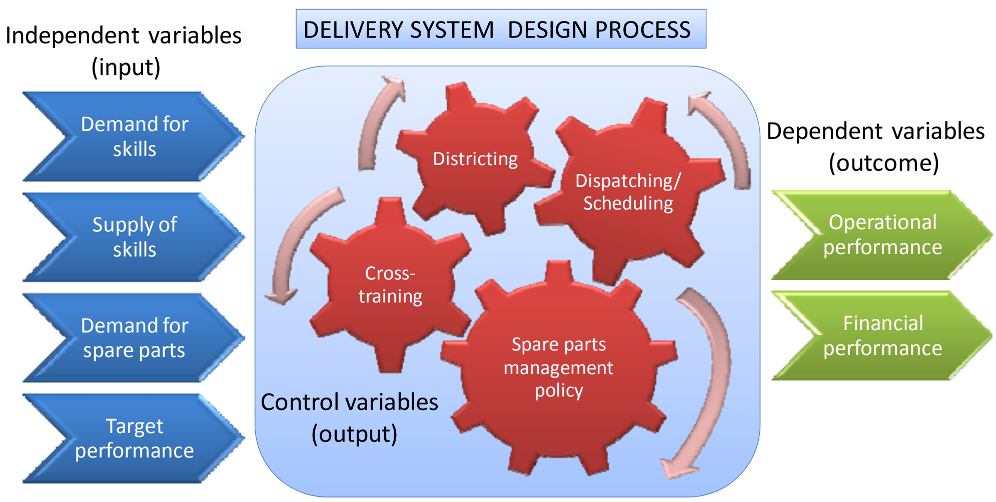

Figure 2: Delivery system design process

Table 1: Independent, control and dependent variables in the delivery system design process

Independent variables:	**Control variables:**	**Dependent variables**
1. Geographical distribution of the demand for skills. It depends on: a. the number of products to serve b. the Mean Time Between Failure of each type of product (and in case the different failure modes) c. the skills required to fix each type of product (and in case the skill required for each failure mode) d. the products' location 2. The current geographical distribution of the supply of skills. It depends on: a. the number of field technicians available b. the locations (home address) of the field technicians available c. the skills mastered by each of field technician 3. Geographical distribution of the demand for spare parts. It depends on: a. number of tasks requiring spare parts b. spare parts/store location c. availability of spare parts 4. The target *operational* and *financial* performance that the delivery system is supposed to meet	a. *Capacity*: number of field technicians to employ b. *Cross-training*: skills to impart to each field technician c. *Districting*: territories to assign to each field technician d. *Dispatching*: algorithm to use to dispatch field technicians e. *Scheduling*: algorithm to use to schedule field technicians f. *Spare parts management policy*: location and quantity of spare parts to keep in inventory	4. *Operational* performance: a. downtime b. response time c. travel time d. answering time e. first contact resolution rate f. SLA compliance g. resource utilization h. etc… 5. *Financial* performance : a. revenues b. costs c. cash flows d. etc…

4. INFORMATION NEED

As can be noticed the independent variables are a set of data that should be easily retrieved from the Enterprises' Information System (EIS).

As a matter of the fact:

1. all the data regarding the installed-base (i-base), the contracts, the service requests, the technicians and the spare parts are usually available in the companies' Enterprise Resource Planning system (ERP system);
2. the i-base is usually geo-referred with Geographical Information Systems (GIS) and the same instruments allow to define the areas the field technicians are assigned to;
3. the product performance in terms of reliability and availability can be easily obtained through statistical tools, starting from the data available in the ERP system, evaluating in particular the functioning time intervals of the machines as the difference between two consequents service requests regarding the same item.

These three sources should provide all the needed data. The information flows that allow the DSS (represented by a simulation tool) to simulate the real situation are shown in Figure 3.

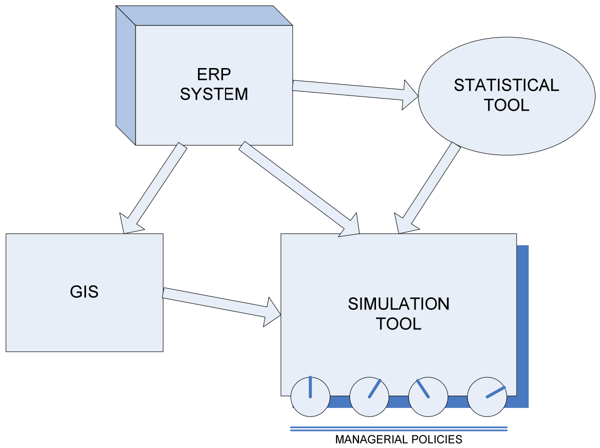

Figure 3: Information flows

5. THE MODEL

A DSS to support the FSDS design should therefore be able to retrieve the required data from the companies' information systems and to perform simulations to test the effectiveness of different managerial policies.

Such a tool has thus to allow to:

- evaluate the variables that are actually relevant in the FSDS designing;
- measure – ex-ante – the effects that the typical decisions taken by service managers could have over the delivery system performance.

Due to the complexity characterizing the field service environment, the methodology adopted for modeling the field service system should be the discrete event simulation (Chung 2003; De Felice 2007; Law and Kelton 2000).

The use of discrete-event simulation, instead of other techniques such as the queuing theory, is fully justified by the number of variables to consider and the randomness of the phenomena to model (Banks 1998; Kelton and Sadowski 2003; Perros 2007).

A representation of the conceptual model that we have developed is shown in Figure 4.

In the model the service requests are entities characterized by several attributes:

- *product type* (and thus the needed technical data);
- *problem type* (and thus the needed skills of the technician);
- *installed base localization* (and thus the needed location of the technician);
- *service level agreement* (and thus the performance constraints);
- *need for spare parts.*

While the process is in progress the data about the problems occurred are computed by the statistical tool and the values of the operating reliability are updated.

Each incoming entity has to be assigned to a technician and could require some spare parts.

Both technicians and spare parts are resources with limited capacity, characterized by attributes such as the geographical location and the service requests they can be used for.

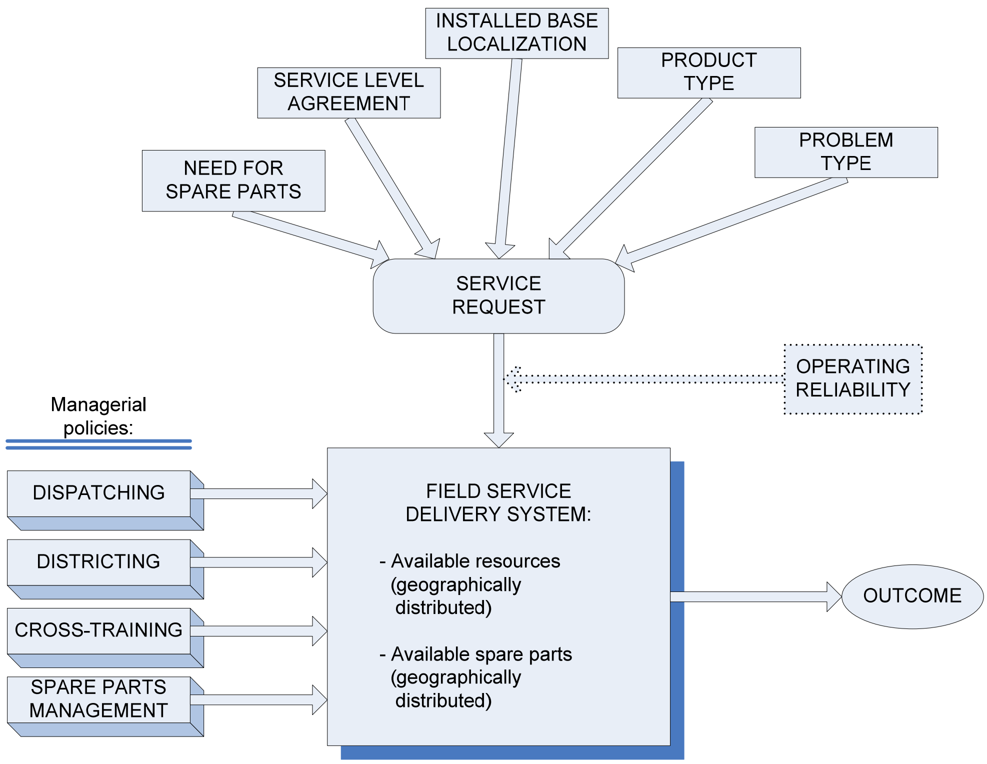

Figure 4: Conceptual model

These resources' attributes depends on the chosen managerial policies. Different policies lead to different values of:

- overall number of field technicians;
- dimension of the area the technicians have to cover;
- skills distribution over the technicians;
- spare parts location and quantity.

The model logic, based on the managerial policies, assign the entities to appropriate resources, creating an entities' flow.

Fundamental element of the simulation model is the dispatching algorithm (implemented in the model logic), that is, the working rule of the model.

This algorithm depends on the values of the control variables and regulates the entities' flow, considering resources' attributes and availability.

It's therefore clear that different managerial policies lead to different algorithms and so to different results of the service delivery process.

The outcome of the process can be finally calculated in terms of:

- resources utilization,
- lead time,
- downtime,
- percentage of fixed requests,
- constraints compliance,
- etc…

The DSS we describe has to be suitable for every kind of company that has to cope with field service delivery problems.

Certainly, each specific application needs some efforts to effectively be able of representing the situation. These efforts aim at analyzing the business processes, evaluating the data availability, defining the rules and the algorithms that are suitable for the case (Pidd, 1992; Ross, 1990).

In general, to create a functional DSS, we have to:

1. develop and verify reliable, flexible and parametric models, able to reproduce "in vitro" different field service delivery systems;
2. validate the models making use of the real data;
3. use the validated models to carry-out scenario analysis and experiments;
4. develop and test algorithms for the scheduling, dispatching and districting optimization by means of the simulation models themselves.

6. CASE STUDY

As a pilot experiment we tried to model the FSDS of a big multinational company that manufactures and services office imaging products.

Through the simulation tool (developed making use of the Rockwell Arena © suite) we have assessed the statistical significance of the effects of the control variables over the overall system's performance.

In order to build and apply the model to the case study, we performed:

- business processes analysis,
- conceptual model of the system,
- data collection and manipulation,
- actual creation of the simulation model,
- experimental design.

The field service delivery process we identified totally follows the model we showed above. We have been able of retrieving all the needed data from the company information system.

In particular, the data we considered are the following:

- service request arrival date and time,
- geographical location of the products (i-base localization),
- characteristics of the products requiring support (product type),
- type of the problems that can occur to each type of products (problem type),
- failure modes and possible solutions,
- needed skills (in dependence of the problem type),
- needed spare parts (in dependence of the problem type),
- skills profiles, availability and work areas of the field technicians,
- instantaneous position of the technicians,
- spare parts availability and location,
- average travel time and work time required to fix the problem,
- target operational and financial performance contractually defined (e.g. Service Level Agreement – SLA),
- service contract validity,
- failure rates characterizing the i-base (operating reliability).

The simplified tool we developed is not able of retrieving automatically the required information from the EIS. We therefore manually extracted the data from the ERP system and the GIS trough worksheets, we performed reliability analysis with a statistical tool and we used the obtained data as an input for the simulation model we created with Rockwell Arena.

After having created the simulation model, we found its stability parameters (Guttman, Wilks and Hunter 1971; Montgomery 2002) and then we performed a Design Of Experiment (DOE) (Box and Hunters 1978; Mood, Graybill and Boes 1974) selecting three of the control variables described above: dispatching, cross-training and districting.

What we did with this variables is perfectly extendible to the complete system, it's just a matter of data amount, time and computational power.

A 2^k DOE analysis showed the influence that changes in the control variables (and in their interaction) give to the overall system's response.

We defined 2 different levels for each control variable and we ran the model in each of the 8 different possible combinations showed in Table 3.

Table 2: Control variables considered in the case study

Control variable	*"+" level*	*"-" level*
Dispatching	STQ	SNQ
Cross-training	High flexibility	Low flexibility
Districting	4 zones	2 zones

Table 2 shows the levels we defined for the control variables.

For the dispatching, the levels are:

- Shortest Time in Queue (STQ) policy, that is, the entity is assigned to the resource with the minimum expected waiting time;
- Shortest Number in Queue (SNQ) policy, that is, the entity is assigned to the resource with the minimum queue length.

For the cross-training, the levels are:

- high flexibility policy, that is, all the field technicians are able of fixing 3 different problem types;
- low flexibility policy, that is, all the field technicians are able of fixing 2 different problem types.

For the districting, the levels are:

- narrow districting policy, that is, a territorial partition in 2 zones;
- broad districting policy, that is, a territorial partition in 4 zones.

Table 3: The 8 variables combinations of the 2k DOE

Case	*Dispatching*	*Cross-training*	*Districting*
A	+	+	+
B	-	+	+
C	+	-	+
D	-	-	+
E	+	+	-
F	-	+	-
G	+	-	-
H	-	-	-

In Figure 5 and 6 the comparison between the different possibilities is shown, considering the mean downtime of the products to serve as a performance indicator.

A treatment is the variation that is felt while passing from the "-" level to the "+" level in each of the three variables (1 – dispatching, 2 – cross-training and 3 – districting), or contemporaneously in more of them (12, 13, 23, 123) (Rotondi 2005).

The proportional variation is the effect that treatments causes on the overall system response.

Treatment	Proportional variation
1	- 9.9 %
2	+ 3.8 %
3	- 8.2 %
12	+ 5.0 %
13	+ 13.6 %
23	- 5.6 %
123	- 7.6 %

Figure 5: Performance variation due to the treatments

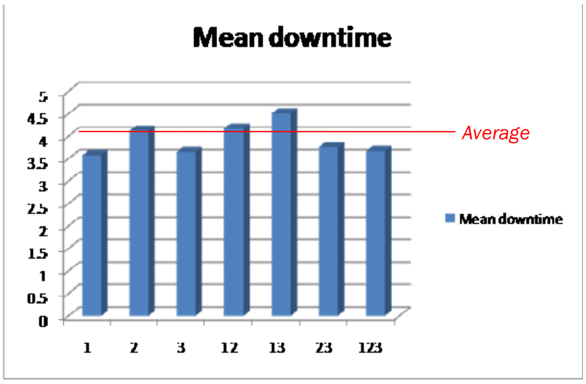

Figure 6: Evaluation of the impact of the considered factors on the performance

The analysis of variance we performed on the simulation model's results, demonstrates that the control variables are statistically significant with a confidence interval of 95%. This says that all the selected factors and their interactions give a significant impact on the performances of the FSDS, so it is correct to analyze them.

In this case the most important element to set seems to be an appropriate dispatching policy (1), followed by a correct districting (3) and then by a proper training and skills spreading policy (2).

We also notice (13) that the performance improvement given by a change in the dispatching policy is much more marked if it is applied together with a broad districting policy (more dispatching alternatives imply higher performance differentials).

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Mario Rapaccini took his Laurea Degree with honors in Mechanical Engineering (5-yr-course) at Florence University in April 1996. He is a professional engineer since 1996. In may 2000 he achieved Ph.D. (3-yr-course) discussing the thesis “Advanced tool for configuration and impact assessment of Integrated Municipal Solid Wastes Management Systems”. Currently, he's assistant professor in SSD ING-IND/35. Research topics covered are: managerial economics and business organisation, ICT, simulation modeling and analysis (SM&A), business process re-engineering (BPR). He's fellow of AiIG, EurOMA, ANIMP, AIRO and ANIPLA.

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