Chapter 7
Enhancing Field Service Operations via Fuzzy Automation of Tactical Supply Plan

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Abstract Tactical supply planning (TSP) is an integral part of the end-to-end field resource planning process. It takes as input, constrained demand from the strategic plan at monthly (or quarterly) level, decomposes it to daily or weekly level and plans the capacity accordingly to meet the expected demand. The plan is then executed and sent to a work allocation system for on-the-day scheduling of individuals tasks to resources. A tactical supply plan ensures that there are enough resources available in the field on any given day. It highlights underutilised resources and offers recommendations on how best to deploy surplus resources. As such, TSP focuses on improving customer satisfaction by minimising operational cost and maximising right-first-time (RFT) objectives.

In this chapter, we describe opportunities and challenges in automating tactical supply planning and present a fuzzy approach to address the challenges. The motivation is to minimise the effort required for producing a resource plan. More importantly, our objective is to leverage computation intelligence to produce optimised supply plan in order to increase RFT and the customer satisfaction.

7.1 Introduction

It is well recognised that one of the key contributors to the success of any firm is the proactive planning of its resources to meet the expected demand. This is crucial for service industries, especially for those with large and dynamic workforces. For them, advance planning of their resources largely determines the cost and quality of

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their services and also their customer satisfaction. These measures also dictate their revenue.

Tactical supply planning (TSP) is an important part of end-to-end resource planning process. It sits between long-term strategic supply planning and the short-term scheduling (Fig. 7.1). Strategic supply planning is typically done for the period of 12–18 months. It looks at expected unconstrained demand for its product and services, typically at monthly level, combines it with different business objectives and makes decisions on how much capacity is to be made available in order to best match the demand and at the same time adhere to various business and financial constraints. The output of this process is the constrained high-level demand for products and services that the business has committed to deliver based on constrained capacity. This is then fed to tactical supply planning which is typically preformed for 1–3 months. It takes constrained demand for products and services at monthly (or quarterly) level, applies various rules to decompose product into individual activities and produces daily or weekly demand at activity level. It also takes any actual demand that is already visible to the firm and combines it with the forecasted demand. These fine-grained demand profiles at activity level are then compared to the available supply and their skills, to make sure that there is enough supply to match the expected demand. At this stage, resource planners have to take into account any shortage (or surplus) in available capacity and optimise the plan so that, on the day, there is enough supply available to execute the tasks.

The output of tactical capacity planning goes to both the reservation system and the scheduling system. Reservation system uses it to make sure that booking for jobs are taken not exceeding the planned capacity. Similarly, the shorter term planning for 1–7 days is used by scheduler where individuals are scheduled according to their planned geography and skills, so that the utilisation of the individuals are maximised and the cost related to their idle time and travel are minimised.

It is important to note that, on one hand, tactical supply plan ensures that there are enough resources available in the field for scheduler to schedule work properly. On the other hand, it also makes sure that there are no resources left unused. As such, TSP contributes heavily to minimising operational cost and at the same time maximising RFT, leading to improved customer satisfaction.

In this chapter, we highlight some of the opportunities and challenges in TSP and present a fuzzy logic-based approach to solve the TSP problem. The motivation is to minimise the effort and the cost of producing plan. We demonstrate how we exploit computation intelligence technologies to produce optimised supply plan in order to increase RFT and customer satisfaction.

This chapter is divided into five sections. Section 7.2 describes the current manual TSP process. Section 7.3 highlights some of the key benefits of its automation. Section 7.4 describes some of the key trends in automating TSP process. Section 7.5 presents a fuzzy approach to TSP. Finally Sect. 7.6 concludes the chapter.

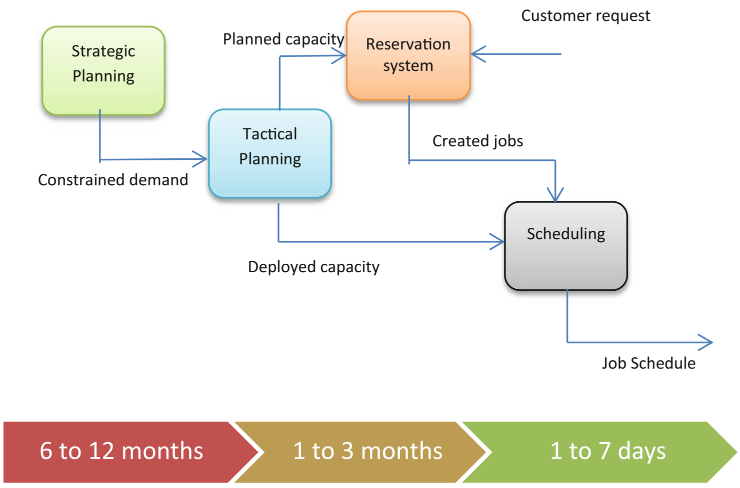


Fig. 7.1 Three stages of resource management

7.2 Current Approaches to TSP

It is well observed that the focus of the service industries mainly revolves around two aspects of supply chain management:

1. Strategic Planning—mainly due to the fact that it underpins finance and budgets which is crucial part of the business planning process
2. Scheduling and Execution—mainly to make sure that the tasks are executed and the customer's request is satisfied on the day

However, despite its importance in the success of end-to-end delivery of services, TSP is often overlooked and poorly managed. This is mainly due to the lack of expertise and the lack of tools and technologies for realising TSP. Current approach to TSP is mainly manual, executed by field resource planners, which involves making informed decisions on the movement of resources between different geographies and skills. This gets complicated with any increase in the number of resources and the types of products and services that a firm offers, consequently the increasing number of skills/areas and the number of plans that has to be balanced. Clearly, this is an optimisation problem, where the goal is to find the best moves that optimise the plan across all skills, geography and time dimension.

In many cases, companies tend to react to capacity imbalances, by bringing in people on overtime or bringing in contingency resources. This reactive approach can lead to inefficiencies and potential failure of customer commitments. Furthermore, even when capacity is managed proactively, it is mainly performed manually, maintained in spreadsheets and using the manual decisions made by the resource planners. For organisations with large number of multi-skilled resources and with many different products and services, such manual decisions are (a) costly and (b) unlikely to be optimal. This clearly highlights the need for an automated approach.

7.3 Benefits of TSP Automation

Below we highlight some of the key benefits of automating TSP process.

7.3.1 Optimal Planning

As mentioned earlier, tactical supply planning can be seen as an optimisation problem. Let's look at a typical scenario when there is a capacity shortage for a particular skill and planner has to plan for the shortage. It is obvious for him/her to look for surplus resources in other plans. Also, resources can only be moved if they are compatible, i.e. if they have secondary skills to do the work in shortage plan. This task of moving resource is trivial when the number of plans is small and resources have only one or two skills. However, when there are multiple plans and resources are highly multi-skilled, possible options for resource movement become large. Let us illustrate this with the figures below:

Here, skills in red are the skills with capacity shortage, skills in blue are with surplus, and skills in green have no surplus or shortages, i.e. they are balanced. Figure 7.2a shows that Skill S2 and Skill S3 have shortages. Skill S2 can take from both Skill S4 and Skill S1 but Skill S3 can only receive capacity from Skill S1. Thus, before making any movement decisions, all of the skills and their dependent skills have to be evaluated. This becomes very complex when many as skills as geographies are involved. Figure 7.2b shows another complication, where Skill S3 can only receive capacity from Skill S2 but Skill S2 does not have any surplus; however Skill S1 or Skill S4, both with Surplus, can give to Skill S2. Here the solution would be to move resource from Skill S2 to Skill S3 and then move resource from Skill S1 or Skill S4 to Skill S2. Obviously, as the number of skills increases, such relationship can become very complex. In such cases any manual movement is unlikely to be optimal. An automated process is therefore required which can intelligently allocate resources and best optimise the plan.

7.3.2 Rapid Scenario Modelling

In most businesses, there are always priorities associated with specific skills (or areas), i.e. there could be skills that can be more business critical than others. There could also be different cost associated with different skills. Similarly, product

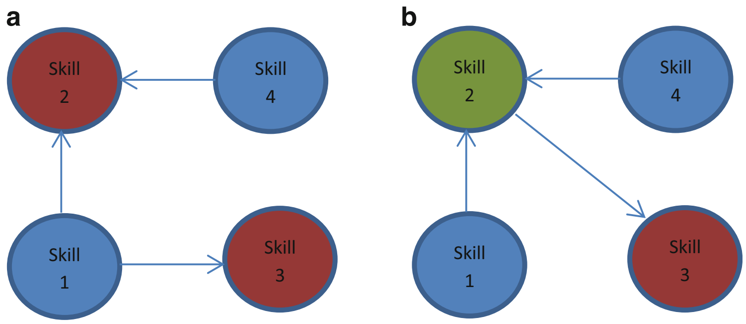


Fig. 7.2 Dependency in multi-skill planning. *Red* colours are shortage skills, *blue* are surplus skills, and *green* are balanced skills. The *arrow* signifies compatibility

offerings may also have different levels of SLAs. And in the situations where there are not enough resources to fulfil the demand for all skills or areas, operational managers will find the best option to utilise their limited supply. They may want to analyse changes in cost and SLA and their effect on resourcing. There could be other multiple 'what-if' scenarios that business may want to evaluate, before making any decisions on supply distribution. Manually setting up these scenarios and testing them could be very time consuming and likely to be suboptimal. Automation of TSP could be very useful for quick scenario modelling and evaluating different supply planning options.

7.3.3 Cost-Effective

As stated above, manual planning process can be time consuming and therefore can be very expensive. Automation can significantly reduce the cost of planning. Further more effective planning leads to effective execution of work and reduction in repeat visits to customers, which in turn delivers cost savings.

7.3.4 Human Error Elimination

Manual processes are prone to human error. Moving non-compatible resources can not only result in capacity waste but also increase the possibility of SLA failure. Clearly, automation using rules would eliminate such errors.

7.3.5 Improved Customer Satisfaction

Also, effective planning means effective and timely delivery of service, which increases customer satisfaction and implicitly helps generate revenue.

7.4 Current Automation: Trends

One of the simplest ways to automate TSP is by using a rule-based systems. They are extensively used in designing and manufacturing industries. They are simple to understand, are easier to build and easier to maintain and can be very effective if specified accurately. The idea is to imitate the human decision-making process by codifying and executing the rules they use in making decisions.

The key properties of any rule-based automation system for TSP are:

1. To allow the user to maintain multiple sets of rules for modelling different scenarios
2. To locate the shortages
3. To locate the surpluses
4. To balance the plan by executing the selected set of rules

Figure 7.3 shows an interface of a rule builder in FieldPlan (Kern et al. 2009; Lesaint et al. 1997, 2000), a resource planning component of Field Optimisation Suite (FOS).

The rules mainly specify the similarities between the skills (or areas) and specify how the system should behave when it encounters a shortage or a surplus, mainly by allowing series of moves to be performed to balance the plan. This approach works well when the relationships between skills (or areas) are simpler. It can also significantly reduce the time needed to perform the planning. However, it is likely that rules defined may not cover all possible shuffles that can arise within specific scenario and hence need for a system that tries to find alternatives rather than those specified in the rule set.

Some of the other sophisticated approaches to TSP include heuristic and meta-heuristic search methods including the Hill Climber algorithm (HCL), the Fast Local Search (FLS), Guided Local Search (GLS) algorithm, Simulated Annealing and Tabu search (Merz and Freisleben 1999; Bianchi et al. 2004; Dorne and Voudouris 2001; Wang et al. 2006). These methods model the TSP problem as an optimisation problem and assign a cost to each planning solution. The goal of these algorithms is to find the solution with the minimal cost. The simplest in this class of algorithms are Hill Climber algorithms. They are simple to implement and have easier workflows. One of the Hill Climber algorithms that was shown to give the best results employs the following steps (Dorne and Voudouris 2001; Shakya 2004):

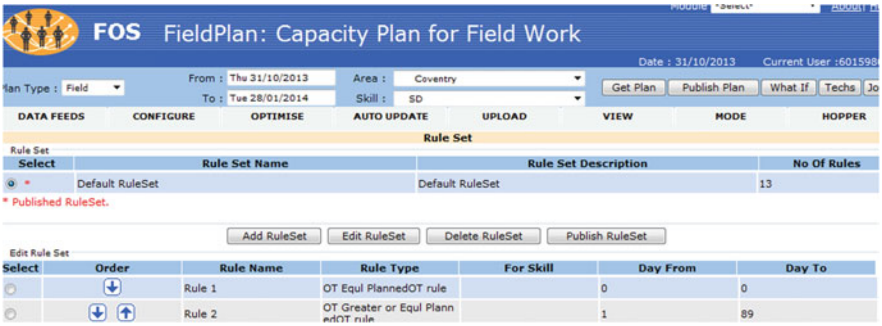


Fig. 7.3 A planning rule creation interface in FieldPlan system

1. Construct an initial solution which is called the baseline plan.
2. Gradually modify and improve the solution until a stopping condition (threshold of cost function value reached, running time expired) is satisfied by:

    (a) Generating the set of moves of resources across possible plans
    (b) Selecting the best move (the one giving the lowest value of cost function) and applying on the current solution

The efficiency of the meta-heuristic algorithm relies on the way the filtering of moves is guided across the search space, that is, the drivers that are used to filter the resource to move and to which plan to assign them (Dorne and Voudouris 2001). Similarly their effectiveness relies on the way the cost function is modelled. It is sometimes very difficult to correctly model the cost function where there are multiple objectives for optimising plan, e.g. minimise the travel of the resources, and at the same time covering the area and skills with higher priority. Using the crisp boundary in defining the cost function (e.g. for defining importance score for area and skill, and maximum travel limit) may not be effective.

In the next section, we describe a TSP planning approach to overcome some of the limitations of crisp algorithms as well as traditional rule-based systems. It is based on fuzzy logic. This approach allows flexibility in defining cost functions and allows greater flexibility in optimising plan.

7.5 Fuzzy Logic-Based TSP

Fuzzy logic is a well-known technique in AI that is use to model the situation where the decision-making logic is not crisp (Hagras 2004; Mendel 2001; Kassem et al. 2012). They are credited with providing transparent methodologies that can deal with the imprecision and uncertainties. For example, a crisp logic clearly distinguishes the difference between a tall and a short person by assuming a crisp point of differentiation, e.g. anyone above 160 cm of height is a tall person.

However fuzzy logic-based model does not have such cut-off point. Instead, it provides a confidence level that says if a person is 155 cm, he/she is short with a certain degree of confidence and tall with a certain degree. And therefore, a height of 155 cm can contribute to both tall and short values for the height variable. This can have different effect to a fuzzy cost function than in a crisp cost function.

7.5.1 Problem Formulation

The key idea for solving TSP is to model the planning process as a fuzzy decision-making process. For the purpose of this chapter, we simplify the problem to skill-based planning; however the method is easily generalised to include both skill- and area-based planning.

In the proposed method, we define two key parameters that formulate TSP problem:

- *Skill priorities*. For every skill a priority is assigned. This is to model the importance of each skill and is used to prioritise demand fulfilment. For example, priorities can be defined by one of Very Low (VL), Low (L), Medium (M), High (H) or Very High (VH). Skill priority is essential as in some cases there could be shortages in more than one skill, and the available surplus might not be enough, in which case, the higher priority skills should be covered first.
- *Skill compatibilities*. For every skill, a list of compatible skills is maintained. This models resources that have more than one skill and therefore can work in any of those skills as required. Also for every compatible skill, a percentage of compatibility is recorded. This percentage represents the percentage of resources that have the main skill but are still capable of covering the compatible skills. This is useful for the case where not all resources have skill to do other jobs.

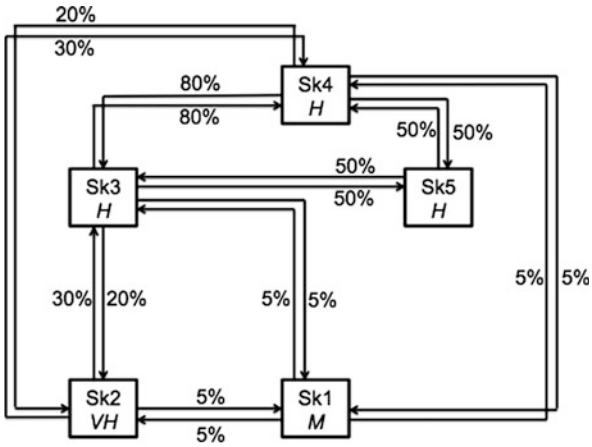
The information on skill priorities and compatibilities can be represented using the graph shown in Fig. 7.4. This is an example of the relations between five skills. Each skill is represented by a square that contains the name of the skill (top of the square) and its priority (bottom of the square). An arrow from one skill to another means that these two skills are compatible. Here, the compatibility percentage is defined by a number on the arrow.

The above information imposes a certain order in performing the moves from one skill to another. For example:

1. It is quite intuitive that the highest priority skill should be addressed first. Then a surplus in any of the skills in the list of compatible skills should be searched for in order to balance the shortage.
2. It is also quite intuitive that the list of compatible skills will be searched in descending order according to the compatibility percentage.

However, this imposed order is not necessarily the order that will balance out the plan, as a skill could be compatible with multiple other skills. Being highly

Fig. 7.4 Priorities and compatibilities graph



compatible may not mean the best one to take from, as other skills may have low compatibility but could be scarce skill. Therefore, giving capacity to such scarce skill first may better optimise the plan. This also means searching for all of the linkages before making decision, which is computationally very expensive. This highlights the need for a logic-based reasoning system that can handle the encountered uncertainties.

The aim of the fuzzy logic system (FLS)-based TSP is to find the best order to perform the set of moves implied by priority and compatibility information.

7.5.2 Methodology

In this section, we will explain the core components of a FLS planning:

7.5.2.1 Parameter Calculation

There are three main parameters that the fuzzy system calculates. All of these parameters are calculated for every possible move for each skill based on compatibility as follows

(a) Highest Surplus: The highest surplus is the highest man hours (MH) of resources that can be given from the source skill to the destination skill. This value is calculated by finding the surplus that the source skill would give if the order imposed by the compatibilities is followed.
(b) Lowest Surplus: The lowest surplus is the least value that is needed from the source skill. This value is calculated by neglecting this skill and finding how much of the shortage would be covered if all the other skills were exhausted. At the end of a processing cycle, if there is still a shortage, then this is the least

value that has to be given by the source skill. For example, if Skill S1 has the option to cover its shortage from skills S2, S3 and S4, where S1 has a shortage of 20 MHs, the surplus skills (S2, S3 and S4) have 10, 10 and 5 MHs, respectively. When we attempt to find the lowest value for S3, we first aim to cover the shortage using the other skills, which means that 15 MHs will be covered (from S2 and S4) and then the lowest value that S3 can give is 5 MHs.

(c) Preference: The preference is a new order that overrides the compatibility percentage, so rather than using this percentage, the compatible skills for one destination skill are ordered in ascending order based on which skill is least needed by other skills.

7.5.2.2 The Type-2 FLS Operation

The FLS processes one move at a time and determines the amount of MHs that will be moved.

(a) Inputs: For every move the FLS takes the highest surplus value, the lowest surplus value and the summation of all the lowest surpluses that are related to the source skill, as input. The third input represents how much the other skills need this surplus. This input is calculated by checking every move in the list of generated moves, if the source skill in that move is the same one as the one being currently processed, the lowest surplus value for that surplus is added to the summation and the final value of the summation is passed to the FLS. Every one of these three inputs is represented using a fuzzy variable that consists of five fuzzy sets: {None, Low, Medium, High, All}. An example of one of the inputs can be shown in Fig. 7.5. The thick lines represent the type-2 fuzzy sets (Hagras 2004) and the dotted lines s represent the type-1 fuzzy sets.

    The fuzzy sets *None* and *All* are singletons, and the rest are type-2 fuzzy sets. Each of the type-2 fuzzy sets Low, Medium and High has a certain number of parameters, for example, the set Low has four parameters, the set Medium has five, and High has four. The universe of discourse is divided equally among the total number of parameters in order to determine the area covered by each set.

    As shown in Fig. 7.5, for every fuzzy input there is a universe of discourse (the range of values on the *x*-axis). For the highest surplus value input, the universe of discourse starts from zero and is bounded by the shortage in the destination skill (MHs). The universe of discourse for the lowest surplus value is also bounded by the shortage in the destination skill. For the third input, ‘the summation of lowest’, the universe of discourse in this case is bounded by the surplus of the source skill.

(b) For every move processed by the FLS, there is a source skill and a destination skill. The destination skill is the one that has the shortage. The source skill is the one that should have the surplus that will cover the shortage. In some cases, the destination skill may have a shortage; however it may have more than one option in order to cover that shortage, i.e. more than one surplus skill. So the main aim of the inference engine is to determine whether this destination skill is

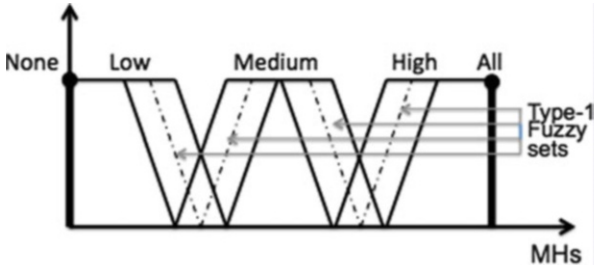


Fig. 7.5 Type-1 and type-2 fuzzy sets representing the highest surplus input

the skill that needs the surplus the most. In the case where the destination skill is not the skill that needs this surplus the most, then the inference determines how much of the surplus this skill takes in order to make sure that there is still surplus left for the other skills (i.e. that need the surplus more).

The first two inputs entered to the FLS (highest surplus and lowest surplus) are supposed to determine how much the destination skill needs the surplus in the source skill. For example, if the highest and the lowest values are quite close, this means that the value in the lowest surplus is absolutely indispensable. However as the value in the lowest surplus approaches zero and the difference between the lowest and the highest grows, this means that the surplus is not really essential to the destination skill—it probably has other options to cover its shortage. We will provide an example to illustrate the above scenario. If we have a destination skill S1 that needs 30 MHs, we have source skills S2, S3 and S4 where each has a surplus of 30 MHs. In this case the highest value for all three will be 30 MHs and the lowest value for all three will be 0 MHs. As the difference between the lowest and the highest is quite big, and the fact that the lowest is 0 MHs, we can get indication that the destination skill has more than one option.

The third input, which is the summation of lowest values, is supposed to represent all the lowest values related to the source skill. So these are the lowest values for all the other destination skills that use this same source skill. This represents how much this source skill is needed by other destination skills. This insight can be used to determine how much of the surplus of this skill can we take in this move, before affecting the other shortages.

After this step, the system determines how much the destination skills need the surplus and how much the other skills need this surplus. The system then uses its rule base to infer how much should be moved.

7.5.2.3 Rule Base

The rule base for the proposed type-2 FLS contains a number of rules. Here are some examples of rules and the underlying logic.

IF Highest Surplus is LOW AND Lowest Surplus is NONE AND LowestSummation is ALL
THEN move NONE

The logic underpinning this rule is—if the highest surplus value that the source skill can give is LOW, and the lowest surplus value that the source skill can give is NONE, the surplus provided by this skill is not only a small amount but it is also dispensable because the lowest value is NONE. This means that this shortage can be covered by other skills. The last input which is the summation of lowest is ALL means that there are a lot of other destination skills that need this surplus. Hence the value to be moved from this surplus is NONE, since this destination skill does not need this surplus and there are other skills that do need it.

Another rule example is as follows:

IF Highest Surplus is MEDIUM AND Lowest Surplus is LOW AND LowestSummation is LOW
THEN move MEDIUM

This rule means if the highest value that the source skill can give is MEDIUM and the lowest value that the source skill can give is LOW, then this destination skill can at least take a LOW percentage of the surplus and at most needs a MEDIUM percentage. The summation of lowest is LOW means that it is ok to take the highest surplus value as there are not many skills that need this surplus. So the value to be moved is MEDIUM.

Another rule example is as follows:

IF Highest is ALL AND Lowest is ALL AND LowestSummation is ALL
THEN move ALL

This rule means if the highest value that the source skill can give is ALL (which means its entire surplus) and the lowest value that the source skill can give is also ALL, then the entire surplus is absolutely necessary to this destination skill and it has no other option. In this case it does not really matter what the summation of lowest is because either way the entire surplus has to be taken by this destination skill.

7.5.2.4 Output

The output of the FLS is the amount to move from each skill to other compatible skills, which is also represented by a type-2 fuzzy variable using five fuzzy sets {None, Low, Medium, High, All}. The universe of discourse is the surplus of the source skill. This suggested move aims to define the optimal movement in order to balance the plan and best utilise the available resources.

7.6 Conclusions

The approach was tested with a field force planning scenario within BT. BT has more than 23,000 field and desk-based technicians. First, these human resources have to be carefully managed and balanced, so that on any given day, there is no shortage or surplus of capacity. Second, they have to be deployed so as to maximise their productivity. BT uses FOS (Field Optimisation Suite) system for automated resource management. FOS consists of a suite of applications that provides end-to-end resource management capabilities, starting from demand forecasting, capacity planning and capacity reservation down to deployment planning and resource scheduling capabilities for the execution day.

A case study was conducted within one of the BT's lines of business. The service area was related to installation and maintenance of telecommunication services. The nature of the work meant they were mainly short duration tasks requiring less than 2 h to complete. The forecasting component of FOS was used to forecast demand volumes. A rule-base system was used to dictate the movement of capacity to match the forecasted demand. The move made by rule-based system was compared against the moves suggested by the fuzzy TSP system. The key measure for comparison was the total collective shortage and surplus MH of capacity against demand for all areas and skills. The closer this value was to 0 the better the performance was—it indicated that the automated planning was able to achieve a balanced plan (i.e. the number of shortage and surplus hours was minimised). The results showed that fuzzy planning approach was able to improve resource balancing in the capacity plan by 6 % in comparison to the rule-based TSP system (Kassem et al. 2012).

Increasingly, organisations are automating their resource management processes. Unfortunately, very little attention has been given to automating the tactical supply planning process (TSP). Automating the TSP process offers opportunities to realise cost minimisation and revenue generation. In this chapter, we have reviewed several different ways to automate TSP process and presented in detail a fuzzy logic-based approach for TSP. The key differentiator here is its ability to smooth the effect of a variable on a cost function and therefore on the overall quality of the plan. The choice of TSP techniques depends on the requirements and size of the organisation.

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