Empowerment-based Workforce Scheduling Problem*

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Abstract

The Workforce Scheduling Problem (WSP) concerns the scheduling of a multi-skilled workforce to geographically dispersed tasks. An effective solution to the problem is critical to companies' performance and success. Organizations are becoming increasingly aware of the importance of enhancing employee empowerment and involvement in decision making. However, traditional approaches implemented to tackle the WSP neglect this concept, despite the fact that employee efficiency is crucial to the effectiveness of any workforce scheduling system. The great benefits promised by empowerment management concepts motivated us to investigate the deployment of empowerment in designing the workforce scheduling system. This paper proposes a new model that applies a constraint satisfaction approach in order to incorporate the empowerment management strategy. A prototype has been developed and its efficiency has been evaluated.

1 Introduction

The workforce scheduling system is a key supportive decision-making system used by organizations to effectively manage human resources [1]. The underlying problem concerns the allocation of jobs to a workforce in an efficient manner, whilst satisfying a large number of operational constraints.

The Workforce Scheduling Problem (WSP) involves both job assignments and routing. It generalizes the well-known Resource Allocation Problem and Vehicle Routing Problem. Several real-life requirements are included, such as multi-skilled staff with various working hours, tasks with different priorities and time-window constraint, route restrictions and multiple depots.

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This problem occurs in a wide range of service companies such as telecommunications, utilities and other networks, in which the field service engineer is a key resource to be managed.

Employees' efficiency is highly critical to the effectiveness of the schedules produced by the workforce scheduling system. This is because time is a coordinate in the process. Unless employees are highly motivated and efficient, they could easily introduce delays which would significantly impact upon the schedule of subsequent tasks, as well as the overall schedule.

Nevertheless, conventional workforce scheduling systems apply traditional management techniques which based on the command-and-control management strategy [2]. These systems, which we refer to as command-based workforce scheduling systems, isolate employees from the decision-making, and leave them powerless in this critical system.

Employee empowerment is another management concept, through which employees are given more control over decisions related to their work. It has been argued that empowerment has promising benefits for both the organization and its employees, offering a win-win approach [3] [4] [2]. Thus, more organizations understand the benefits of enhancing, rather than minimizing, employees' contribution, power and control, with the desire to increase productivity and quality, as well as enhance employee motivation and retention.

Involving employees in the allocation decision within the workforce scheduling systems could incorporate the great benefits promised by empowerment, as suggested by Tsang et al [5]. It could also provide another motivation source for employees, which are normally limited to pay and bonus schemes.

We propose a new model for designing workforce scheduling systems. The new system, which we refer to as empowerment-based workforce scheduling systems, attempts to implement the empowerment management concept by deploying a Constraint Satisfaction Approach [6] to provide employees with a form of involvement in the decision-making.

Whilst we have chosen to examine the model in relation to WSP, it is believed that this model has the potential to be generalised for use with other staff-job allocation problems. Moreover, it could be extended to other variants of personnel resource allocation problems such as timetabling.

This article is organized into seven sections. Command-based (i.e. traditional) WSP will be described and formulated in section 2. Section 3 will introduce empowerment as a management concept. We will discuss and formulate the Empowerment-based WSP in section 4. The prototype will be explained and the experimental results will be discussed in sections 5 and 6. The conclusion and suggestions for future work will be in section 7.

2 Command-based WSP

Conventional workforce scheduling systems apply a command-and-control strategy in managing human resources, where the system assigns jobs to an employee who has only to accept the decision. The underlying optimization problem focuses mainly on optimizing the organization's objective(s). This focus excludes employees from the decision-making, which could affect the optimality of the organization's objective(s).

Problem formulation is a very important step which is often underestimated [7, 8]. Modelling formalizes the problem's considerations and objectives. Below an attempt to rigorously formulate the Command-based WSP can be found.

2.1 Problem Formulation

The traditional Workforce Scheduling Problem ($command - baseWSP$) is basically the problem of allocating a set of technicians (resources): $R = \{r_1, r_2, ..., r_N\}$, to a set of tasks: $T = \{t_1, t_2, ..., t_M\}$. A task t is described by a tuple:

$$< c_t, dur_t, s_t, [bt_t, et_t], l_t >$$

Where (c_t) is a predefined priority which determines its importance to the company. The higher the value of c_t the more important the task will be, and $c_t \in \Re$. dur_t is the expected duration a technician requires to finish this task. Each task requires a technician with a particular skill $s_t \in S$, where S is the set of all skills: $S = \{s_1, s_2, ..., s_K\}$. A task t must be serviced within a predefined time window described by $[bt, et]$. Tasks are geographically distributed, and the location of a task is denoted by ℓ_t.

Each technician $r \in R$ is described by the following tuple:

$$< [br_r, er_r], S_r, \ell_r >$$

Each technician has a fixed shift hours where the begining and end of the shift is expressed by $[br, er]$. S_r denotes the skill(s) a technician has, where $S_r \subseteq S$. There is no a single depot for technicians to start from, as they can start from home or from one of predefined depots. The location of a technician is denoted by ℓ_r.

The travelling time between any two locations ($TD_{\ell_1 \ell_2}$) is calculated as the Euclidean distance divided by speed (υ).

There are two sets of decision variables in WSP: the allocation variables $X = x_{ij}|i = 1, \cdots, N; j = 1, \cdots, M$ and the service times $F = f_i|i = 1, \cdots, M$. A variable x_{ij} is equal 1 if technician r_i is allocated to task t_j, and 0 otherwise; where a variable f_i denotes the actual service time of the task t_i.

Having decided these variables, a set of routes $\pi = \{\pi_1, \pi_2, \cdots, \pi_N\}$ are defined. A route π_i is a sequence of tasks ($\subseteq T$) that are to be visited by technician r_i; $\pi_i = (\pi_{i1}, \cdots, \pi_{i\sigma_i}), 1 \leq \sigma_i \leq M$. We define two functions, namely $first(\pi_i)$ and $last(\pi_i)$ which denote the first task (π_{i1}) and the last task ($\pi_{i\sigma_i}; 1 \leq \sigma_i$) of the route π_i, respectively.

The main objective is to find an assignment of resources to tasks that maximizes the number of allocated tasks with respect to thier priorities, while satisfying all assignment and routing constraints. This paper consider this objective for the WSP. There are other objectives which can be considered as well, such as minimizing the total traveling distance, and resources' load balancing.

The command-based Workforce Scheduling Problem can, then, be mathematically modeled as follow:

$(command - based \quad WSP)$

$$max \sum_{r \in R} \sum_{t \in T} c_t x_{rt} \tag{1}$$

subject to

$$\sum_{r \in R} x_{rt} \leqslant 1 \quad \forall t \in T \tag{2}$$

$$s_t \in S_r \quad \forall x_{rt} = 1, t \in T, r \in R \tag{3}$$

$$bt_t \leqslant f_t \quad AND \quad f_t + dur_t \leqslant et_t \quad \forall t \in T \tag{4}$$

$$f_{last(\pi_r)} + dur_{last(\pi_r)} \leqslant er_r \quad \forall r \in R \tag{5}$$

$$f_{first(\pi_r)} \leqslant br_r \quad \forall r \in R \tag{6}$$

$$br_r + TD_{\ell r \ell_{first(\pi_r)}} \leqslant f_{\pi_{r1}} \forall r \in R \tag{7}$$

$$f_{t_i} + dur_{t_i} + TD_{\ell_{t_i} \ell t_{i+1}} \leqslant f_{t_i+1} \quad \forall t_i \in \pi_r, t_i \neq last(\pi_r); \forall \pi_r \in \pi \tag{8}$$

The objective function is represented by (1). Constraint (2) impose that each task is visited at most once. The skill constraint is expressed in equation (3). The time window constraint of all tasks is assured by (4). (5) and (6) ensure that all tasks which are assigned to a technician must be within the technician's working time. Finally, Equations (7 and 8) ensure route validity by considering the travelling time between a technician's base location and the first task, as well as between subsequent tasks in technician's route.

3 Empowerment

3.1 What does empowerment actually mean?

Empowerment as a management concept is an elastic term which is loosely defined and used [9] [2]. Although it has been widespread since the 1980s, there is no precise definition of empowerment in the literature. Essentially, employee empowerment is a management concept through which employees are given more freedom and flexibility to make decisions related to their work.

Two conceptions of empowerment are reflected in the literature [4] [2] [10] [11]. The first approach conceptualizes empowerment as a managerial relation, and defines this term as the process of enhancing employees' authority and control over decisions related to their tasks. From this perspective, empowerment is a broad concept which encompasses other management ideas such as delegation, job enrichment, decentralization of decision making and participatory management. The second approach, however, emphasizes the psychological values of empowerment, and refers to empowerment as the process of enhancing the motivational concept of self-efficacy. Other researchers tend to combine the two approaches, viewing empowerment as enhancing both employees' decision power and self-efficacy.

The moralistic theme beneath empowerment language was discussed by Claydon and Doyle [3]. They ethically examined the two messages comprised in the term empowerment, namely the "soft" message (i.e. enhancing autonomy and self-discretion) and the "hard" message (i.e. accountability and ownership). They argue that empowerment language is found between the ethical theories of deontology and egoism.

3.2 Benefits of Empowerment

The empowerment literature delivers convincing arguments concerning the benefits of employee empowerment [12]. Empowerment is seen to be beneficial both for the organization and employees. As Greasley et al (2005) summarizes, the benefits for an organization are the remarkable improvements in cost control, flexibility, productivity and quality; where the benefits of empowered employees are enhanced job satisfaction, motivation and organizational loyalty. These mutual benefits present a win-win scenario which is considered the main motivation in making a move towards empowerment [3].

The literature is rich with success stories from organizations that have embarked on this journey (see for example, [13] [14] [11] [12]). However, such appealing benefits can not be attained without costs, both in terms of establishing a new approach to management (involving training costs, costs of new reward and information systems) and in its operation (involving issues of integration, consistency and unintended consequences) [9].

3.3 Employee's Perception of Empowerment

Researchers have predominantly focused on the management perspective while studying empowerment. However some research has been conducted to study the employee perception of empowerment, for instance [2]. Wilkinson [9] stated that "It is taken for granted in much of the prescriptive literature that employees will welcome and indeed be committed to the new approach. Indeed there is evidence that workers welcome the removal of irritants (e.g. close supervision) and welcome the opportunity to address problems at source as well as the ability to decide work allocation." Yet it has been argued that employee's perception and commitment varies according to several factors such as education, experience, skilfulness, and personal characteristics [10] [14].

3.4 Review of the Empowerment Literature

Most empowerment practices are principally human-centric, in which the amount of redistributed power, alongside the exercises and effectiveness of the empowerment strategy depend entirely on the people in the organization, i.e. managers and employees.

It is possible to say that the contribution of technology to this management style is still modest. The main reason behind this is that the empowerment practices suggested in the literature focus on enhancing employees' power and control over task-related decisions, but have not to any great extent been extended to include decisions made by supportive subsystems, particularly the task-assignment system.

Efficient extensions to the scope of practices associated to empowerment to include such decision-support subsystems would, on one hand, create more opportunities for employees to get involved. On the other hand, it could be beneficial for those supportive systems to apply new decision-making strategies that could help improving the service quality.

3.5 Empowerment initiatives in resource scheduling

Before reviewing the models in resource scheduling literature that made an attempt to apply the empowerment management strategy, it is important to define what constitutes empowerment in workforce scheduling problems. We define this as an empowerment-based model should recognize the individuals' self interest, which is somehow reflected in the final plan.

There have been few attempts to implement the empowerment approach in computerized decision support systems in general, and workforce scheduling in particular. It has been reported that an online voting system was used as an empowerment practice, through which employees are given a set of activities and allowed to vote online for the activities they most wish to do [13]. Although voting systems are normally designed to support industrial democracy, it can also be considered as a supportive practice to involve workers in the decision-making process. Nevertheless, this technique is suitable for the teamwork, rather than the individual, context where democracy could be a very practical practice. Moreover, the workforce scheduling problem usually deals with very short-term, partially dynamic jobs, in which there is no sufficient time to utilize this technique.

Employees' preferences are considered in some models which were proposed to solve scheduling problems, see for example [15] [16]. In these models, employees can express thier preferences by associating weights to a particular property of tasks such as its requirement. Although one could claim that employees' preferences is an empowerment practice, we consider it as a consideration more than involvement, as employees have no explicit authority or control over the decision making. Furthermore, the scope of preference is normally limited to a single attribute of the task undertaken, such as its type or its location, which could weaken employees' feelings of power and motivation, and consequently their self-efficacy.

The first explicit initiative that adopted empowerment in solving workforce scheduling was introduced by Tsang et al [5]. Their approach was to model the problem's entities (e.g. manager, engineers, and jobs) with intelligent agents, each of which has its own interests which are in conflict with others. This approach formulates the problem as a distributed scheduling problem, allowing each agent to look at its interests, while the manager agent looks at the company's interest. Giving engineers the chance to pursue their interests is claimed to be the empowerment practice in this model.

However, two main reasons make this model more appropriately implemented at the dispatcher's or probably team leaders' levels, than the individuals. Firstly, engineers' powers to attain their interests are strongly controlled by the manager agent who generates the weights of engineers' objectives. A schedule is generated as a response to the manager's decision of the objectives' weights; hence, engineers can not anticipate their plans. Secondly, the difficulty of the manager's optimization problem increases with the number of agents. Thus, implementing individual agents would impact upon the manager's optimality.

In our research, we intend to develop a model that implements the empowerment management style. The model focuses on formulating the problem as to give employees an explicit control over the decision making. The following section describes our proposed model in detail.

4 Empowerment-based Workforce Scheduling System

Empowerment in practice is a form of employee involvement designed by management with the purpose of boosting workers' contribution and commitment to the organization [9]. Applying the empowerment management approach to workforce scheduling requires designing a flexible, efficient model that increases employee involvement in the allocation process.

In order to deploy the empowerment management concept in the workforce scheduling problem, employees should be involved in the scheduling process and their control over their work should be increased. This can be attained by enabling them to express their preferences and submit daily plans that can be considered in the allocation process.

From the optimization perspective, this involvement would, theoretically, negatively affect, to various extents, the scheduling optimality with respect to the organization's objectives. However, the improvement in service quality and productivity which are promised by the empowerment style motivates the implementation of this management concept.

4.1 Work Plans: The Empowerment Vehicle

A key element in any empowerment-based scheduling system is the representation of employee involvement, which defines the employee's decision power. In workforce scheduling problems, employees would like to be empowered to have decision power allowing them to influence the assignment of jobs to them. If one thinks about the possible scenarios in which an employee would use the power, one could categorize these scenarios into three planning categories:

1. **Short-term plan:** an employee might want to plan for the next job e.g. "I do (not) want to take this particular job due to its requirement or location".

2. **Long-term plan:** an employee might want to plan for a particular day, e.g. "I want to finish my shift at a particular area/location, today I want to be allocated to jobs located in a particular area, or today I want to do only jobs that are of a particular skill(s)".

3. **Preference:** an employee might have preferences he or she would like to be considered in an everyday plan, e.g. "I prefer to work in this area where I usually have family commitments, or I prefer to do jobs that are of a particular skills".

This classification of possible scenarios suggests that the representation of employee involvement in the decision making can be expressed in terms of work plans. A work plan (WP) is a general term which can encompass most possible scenarios. It is the vehicle of empowerment in our model, which an employee can utilise to express his/her preferences.

Naturally all plans can be expressed as a constraint relationship [6]. These constraints will be considered to be satisfied in the scheduling process. Workforce scheduling problems are very complex, subsequently, the promise of satisfying all the plans cannot be guaranteed. Thus an employee's work plan is a soft constraint which can be violated at an incurred cost. In this case the task becomes finding a schedule that satisfies the majority of constraints, rather than all the constraints.

Associating a cost to each plan allows our model to be cope with situations where employees may vary in their power. This variance could be consider as a motivation source for employees, which are normally limited to pay and bonus schemes.

The empowerment practice introduced above changes the nature of the problem. The underlying optimization problem is reformulated to look at not only the organization's objectives, but also to the employees' interests. Thus, the scheduling problem comprises two sub-problems: an optimization problem that maximizes the organization's objective, subject to the operational constraints, and a constraint satisfaction optimization problem that minimizes the unsatisfied work plans.

4.2 Problem Formulation

Every technician $r \in R$ is able to provide a work plan wp_r per day. A plan is basically a constraint (ρ) by which a technician can describe the jobs he/she wants to undertake. For instance, a technician r might want to be allocated to jobs of a particular set of skills, or jobs in a particular region. Each plan is associated with a weight (ω) to determines the incurred cost of failing to satisfy this plan, in cases where the employees vary in their power over the decision-making process.

An indicator y is defined for the empowerment-based WSP. The indicator y_r ($\forall r \in R$) is equal 1 if the plan ρ_r is satisfied, and 0 otherwise.

As a result, the change this model will make to the formulation of the WSP (section 2.1) is the addition of another objective function; thus, the WSP becomes a bi-objective optimization problem, where the task is not only to maximize the number of jobs served, but also to satisfy the maximum number of technician's plans. The mathematical formulation of the empowerment-based WSP will be similar to that of the command-based WSP, with the addition of the new elements which can be defined as follows:

$$wp_r \quad = \quad < \rho_r, \omega_r > \quad \forall r \in R, \quad 0 \leqslant \omega_r \leqslant 1 \tag{9}$$

$$max \sum_{r \in R} y_r \omega_r \tag{10}$$

5 Prototype

For the model outlined above, we have implemented an initial prototype in which the complexity of the model is slightly reduced. Referring to the formulation of the empowerment-based WSP, the initial prototype assumes that all employees are of an equal power (i.e. all plans are of the same weight). We intend to always examine the tightest scenario, where every employee has a plan to be considered.

5.1 Plan Generator

A major element in our experiment design is to model employees' plans. A plan is a constraint that limits the possible values a variable can take. Employees toned to be able to describe jobs that they want to be allocated. There are three main properties that can be used to describe a job, namely the job's id, type (i.e. required skill), or location.

Our model is based on these properties, such that each plan uses a property to describe the tasks that the corresponding employee wants to do. When an employee wants to do particular tasks or tasks of a particular skill(s), the employee just needs to determine the tasks' id or the skill(s) codes, respectively. In terms of location, the whole service region of the WSP is clustered into several areas which can be used by an employee to limit the jobs that will be allocated to him to particular area(s).

Given the sets of technicians R, tasks T, skills S and areas $Areas$, and the number of tasks, on average, a technician can perform on a daily shift avg_{tr}, the plan generator is outlined as follows:

Plans Generator($R, T, S, Areas, avg_{tr}$)

for each r_i such that $1 \leqslant i \leqslant N$ **do**
    $P \leftarrow Random(\text{"}id\text{"}, \text{"}skill\text{"}, \text{"}location\text{"})$
    if $P = \text{"}id\text{"}$ **then**
        $size \leftarrow Random(avg_{tr} \cdots 2 * avg_{tr})$
        $D_p = Random(d | d \subseteq T, |d| = size)$
    else if $P = \text{"}skill\text{"}$ **then**
        $size \leftarrow Random(1 \cdots max(|S_{r_i}|, |S|/2))$
        $D_p = Random(d | d \subseteq S_{r_i}, |d| = size)$
    else if $P = \text{"}location\text{"}$ **then**
        $size \leftarrow Random(1 \cdots |Areas|/2)$
        $D_p = Random(d | d \subseteq Areas, |d| = size)$
    end if
end for

The plan of an employee is generated randomly. First, a property will be chosen randomly, which can take three possible values: "id", "skill" or

Table 1: The probability distribution used to sample the number of skills for each technician.

Number of Skills:	1	2	3	4	5	6	7	8	9	10
Probability:	0.02	0.05	0.08	0.15	0.20	0.20	0.15	0.08	0.05	0.02

"location" which makes the plan describes tasks by their identifier, skill requirement or location, respectively. Accordingly, the size of the domain values is drawn randomly within a specific range. This range is calculated as a function of the number of tasks, on average, a technician can perform on a daily shift for the "id", the size of the employee's set of skills for "skill" or the number of areas that construct the whole service region for "location". Finally, a subset of corresponding set to the chosen property is randomly selected to be the domain values.

5.2 Problem instances

We developed a problem generator which is partially inspired by a real WSP. Instances are constructed as follows: We measure the duration of a day in the number of minutes from midnight. A day typically starts at 480 (8:00 am) and ends at 1060 (5:40 pm), i.e. $[br, er] = [480, 1060]$. We assume that all technicians have only a full-day shift, to minimize noise.

In a real scenario, a region manages 86 technicians ($M = 86$), and receives on average about 260 tasks per day ($N \simeq 260$), of which 222 are appointment (i.e. normal priority, $c_{np} = 10$) tasks. For appointment tasks, we distinguish between a whole day task (which can be done anytime during the day) a morning task which should be finished by 13:00 o'clock and an evening tasks which cannot be started before 13:00. In the experiment, we set the time window of a task, $[bt, et]$, to be (480, 1060) with 0.5 probability, (480,780) with 0.25 probability and (780, 1060) with 0.25 probability. On the other hand, high priority tasks ($c_{hp} = 20$) start differently during the day, all of which must be served within 180 from the time it starts (i.e $et - bt = 180$).

Each task requires a technician with a particular skill. We distinguish between ten different skills ($|S| = K = 10$), abbreviated: $s_1 \cdots s_{10}$. Each technician can have one or more skills. In our experiment, the number of skills that technicians in the workforce have (denoted by μ) follows a binomial-like distribution as given in Table 1.

The type of skills for both tasks and technicians is sampled uniformly at random from $s_1 \cdots s_{10}$.

The time required to finish a task (dur_t) varies as a function of the associated skill. This is modelled as a triangular distribution. However, we consider in this paper a simple scenario, in which the duration of all tasks, by default, is equal to 95.

We consider a 80 km^2 region. The density of tasks over this region is based on real geographical distribution of houses. We assume that technicians start the working day from home. The location of all tasks as well as the initial locations of all technicians are chosen uniformly at random from the region. Travel time (between any two coordinates) is measured as the Euclidean distance divided by speed (v). We are particularly interested in highly constrained travel times and hence we assume that the speed (v) is 5 km/h.

5.3 Algorithm

The aim of the workforce scheduling algorithm is to find a feasible schedule of high-quality with respect to the main objective. However, most of the real-world scheduling problems are combinatorial optimization problem in which using complete search methods (e.g. branch & bound method) to find the optimal solution in a reasonable time is not possible. Thus, it is usually the case that one sacrifices completeness and look for a near-optimal solution at reasonable time.

Two major approaches which use this strategy have been successfully applied to workforce scheduling problems, namely metaheuristics [17] such as Guided Local Search [16], the Genetic Algorithm [18], Simulated Annealing [19] and Constraint Logic Programming [20, 21]; and rule-based systems [22, 23]. Among these approaches, Guided Local Search obtained the best results on a benchmark problem [16], which motivates us to study the application of Guided Local Search to the empowerment-based WSP.

5.3.1 The Basic Local Search

Local Search (LS) is the basis of most heuristic methods including GLS [17]. Follows are the four main components need to be defined to apply LS to the empowerment-based WSP:

Solution Representation. Each candidate solution, i.e. state, in the search space is represented by a permutation of M tasks. Such a permutation specifies the order of tasks to be considered in the scheduling process. The first task in the permutation is scheduled first, then the second one, and so on and so forth. Scheduling a particular task follows a deterministic procedure which can be summarized as allocate this task to the nearest technician with respect to all constraints and employees' plans.

Neighbourhood Function. The Neighbourhood function is defined as any new permutation that may be obtained from the current permutation by a single swap between any two tasks.

Cost Function. By using the weighted-sum approach, the cost function for the empowerment-based WSP will be the aggregation of the two optimization functions defined in Equations (1) and (11):

$$f(s) = w_1 * \sum_{r \in R} \sum_{t \in T} c_t x_{rt} + w_2 * \sum_{r \in R} y_r \omega_r$$

The initial solution. The initial solution is generated heuristically based on three rules:

1. High priority tasks are scheduled first. This rule is very practical since the objective function takes into consideration the priorities of tasks (c_t).
2. For two tasks t_i, t_j with the same priority (i.e. $c_{t_i} = c_{t_j}$), if the number of available and qualified engineers for t_i is less than that for t_j, then t_i is scheduled first, otherwise t_j (i.e. Smallest-domain-first, SDF).
3. For two tasks t_i, t_j with the same priority and domain size, the shorter in terms of estimated duration dur_t is scheduled first (i.e. greedy principle).

5.3.2 Guided Local Search

Guided Local Search (GLS) is a general metaheuristic algorithm for optimisation [24]. GLS sets on top of local search with the purpose of escaping from local minima by using penalty-based approach. The basic idea is to augment the objective function with penalties, which direct the search away from local optimum. Thus, GLS uses a function $h(s)$ in the search process instead of the main objective function, $f(s)$:

$$h(s) = f(s) + \lambda \sum_{i \in F} p_i * I_i$$

In this formula, s is a candidate solution and λ is a parameter to the GLS algorithm. F refers to the number of features in s. p_i is the penalty of feature i (each p_i is initialized to 0), and Ii is an indicator: $Ii(s) = 1$ if s exhibits the feature i; 0 otherwise.

In the empowerment-based WSP, $f(s)$ is an aggregation of two functions with different weights and, thus, two sets of features will be defined. As minimizing the total unallocated tasks is an objective, the inability to serve a task is characterized as a feature to be penalized. Thus, the first set of features F_1 has N features, where N is the total number of tasks. The second objective concerns minimizing unsatisfied employees' plans and, therefore, the second set of features F_2 are characterized by the inability to satisfy plans. There are M features in F_2, where M is the total number of employees.

Each feature is associated with a cost to help GLS choosing features that have more influence on the cost function in order to penalize them. We consider the task priority as the cost of features in F_1, in order to give high priority tasks more importance; whereas all features in F_2 are of an equal cost, due to the assumption that all employees have the similar power. p_i is the penalty of feature i (each p_i is initialized to 0), and Ii is an indicator: $Ii(s) = 1$ if s exhibits feature i; 0 otherwise.

As a result, the augmented objective function $h(s)$ is expressed as follows:

$$h(s) = w_1 * [\sum_{r \in R} \sum_{t \in T} c_t x_{rt} + \lambda_1 \sum_{i \in F_1} p_i * I_i] + w_2 * [\sum_{r \in R} y_r \omega_r + \lambda_2 \sum_{i \in F_2} p_i * I_i]$$

The weighted-sum method applied to transfer the two objectives functions into a single function, is also propagated to the corresponding set of features. We, moreover, defined two parameters of the GLS λ_1 and λ_2; however, the empowerment-based WSP was found, through empirical analysis, not to be sensitive to those parameters.

6 Results and Discussion

In this paper, we aim to examine the new model, in comparison to the command-based model. This includes examining the cost of different level of employees' power over the scheduling decision on the company's main objective (i.e. productivity objective), and the ability of this model to provide an efficient empowerment practice.

To attain this aim, we ran the GLS algorithm on 20 problem instances, for each of which different sets of weights W were tested, such that $W \in \{(a, 1-a)|a \in \{1, 0.8, 0.6, 0.5, 0.4, 0.2, 0\}\}$ and a is the weight given to the productivity objective (Equation 1). At one extreme, $a = 1$ (i.e. $W = (1, 0)$) represents the command-based WSP, since the empowerment objective (Equation 10) is ignored in the optimization process. And as a decreases, the influence of the empowerment objective on the optimization process should increase.

Since the plans generator is based on a stochastic model, five different instances of employees' plans were tested for each weight setting.

For the purpose of this paper, we use the actual cost of each objective rather than the aggregation of both objectives. We measure, for each weight setting, the mean of 20 instances, and for each one measure the mean of five runs with different employees' plans.

The results are given in Table 2 which describes the mean cost of each objective for each weight setting. For simplicity, the productivity objective

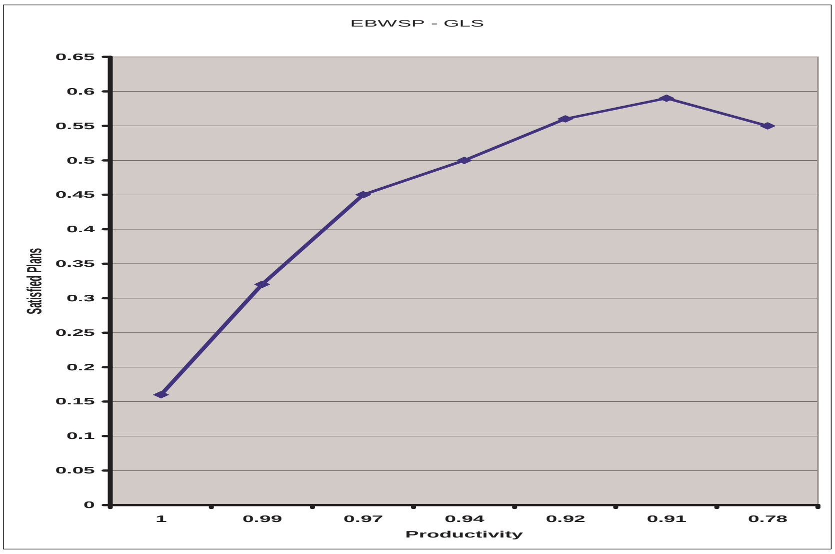

Figure 1: The correlation between the empowerment objective and the productivity objective.

is normalized. The correlation between the normalized productivity cost and the empowerment cost is plotted in Fig1, which shows the cost of satisfying employees' plans on the company's main objective.

Table 2: The mean cost of each objective for each weight setting

Weight Setting (Pro,Emp)	Productivity	Productivity(Normalized)	Empowerment
(1,0)	0.94	1	0.17
(0.8,0.2)	0.93	0.99	0.33
(0.6,0.4)	0.9	0.96	0.45
(0.5,0.5)	0.88	0.94	0.5
(0.4,0.6)	0.86	0.91	0.56
(0.2,0.8)	0.83	0.88	0.58
(0,1)	0.74	0.79	0.51

The results reveal the efficiency of this model which shows its ability to consider the plans from all employees and satisfy 58% of them. This is achieved at the expense of losing 12% of the productivity objective. The inability to satisfy all plans is expected and this is due to either the existence of conflict between multiple plans, in which only one of them can be satisfied, or to the inability of the optimization algorithm to obtain the global optimum solution.

Furthermore, the results encouragingly show that even if the empowerment objective is ignored (i.e. the traditional WSP); about 17% of all plans can be satisfied without any effect on the productivity objective.

Interestedly, when the GLS optimizes only the empowerment objective, it could not obtain the best cost with respect to this objective. This can be attributed to the many local minima in the landscape of the empowerment objective which traps the GLS. To illustrate this, the size of the search space for the problems used in the experiments is about 260!, the domain of values for the cost of each of which range from $0 \cdots 90$. Therefore, introducing another objective to be aggregated with a small weight changes the landscape and helps the GLS to explore more spaces.

7 Conclusions and Future Work

The Workforce Scheduling Problem (WSP) is a complex combinatorial optimization problem. Employees' efficiency is very critical to the effectiveness of any scheduling system; however, conventional formulations of WSPs exclude employees from the decision-making process.

Empowerment is an alternative management concept, through which employees are given more control over decisions related to their work. Enhancing employee efficiency is a major benefit promised by empowerment, which motivates us to incorporate this management theme in designing the WSP.

The empowerment-based WSP is a new formulation of the WSP, which implements the empowerment management concept by incorporating ideas from the constraint satisfaction discipline. This formulation considers the two constitutions of empowerment in WSPs, namely recognizing individuals self interest and enhancing individuals' feeling of empowerment which can be attained when their plans are reflected in the final schedule.

Based on this new formulation, a prototype has been developed to prove the concept that the formulation satifies the two constitutions of empowerment. A Guided Local Search was proposed to solve the underlying optimization problem in this prototype. Experiments were conducted to analyse the efficiency of this new approach, in comparison to the traditional formulation. The results showed the efficiency of this model, demonstrated by the ability of GLS to satisfy about 58% of all employees' plans at the expense of sacrificing 12% of the company's main objective.

The empowerment-based WSP is a constrained multi-objective optimization problem in nature. In this study, we rather transformed the problem to a single objective optimization problem by using the weighted-sum approach. However, the multi-objective optimization literature is rich with efficient techniques that can be applied to the empowerment-based WSP.

We developed a stochastic model to simulate employees' plans. We intend to investigate other stochastic or heuristic models in order to examine the robustness of this formulation, alongside any proposed algorithm, in relation to changes in the employees' plans.

References

[1] Voudouris, C., Owusu, G., Dorne, R., Lesaint, D.: Service Chain Management: Technology Innovation for the Service Business. Springer Berlin Heidelberg (2008)

[2] Greasley, K., Bryman, A., Dainty, A., Price, A., Soetanto, R., King, N.: Employee perceptions of empowerment. Employee Relations **27**, 354–368 (2005). Doi:10.1108/01425450510605697

[3] Claydon, T., Doyle, M.: Trusting me, trusting you? the ethics of employee empowerment. Personnel Review **25**, 13–25 (1996). [1] [1]

[4] Conger, J.A., Kanungo, R.N.: The empowerment process: Integrating theory and practice. The Academy of Management Review **13**(3), 471–482 (1988)

[5] Tsang, E.P.K., Virginas, B., Gosling, T., Liu, W.: Multi-agent systems for staff empowerment. In: Service Chain Management, pp. 263–272

[6] Tsang, E.: Foundations of Constraint Satisfaction. Academic Press, London and San Diego (1993)

[7] Borrett, J., Tsang, E.: A context for constraint satisfaction problem formulation selection. Constraints **6**(4), 299–327 (2001). 593341

[8] Fink, E.: How to solve it automatically: Selection among problem-solving methods. In: 4th Int. Conference on Artificial Intelligence Planning Systems (1998)

[9] Wilkinson, A.: Empowerment: theory and practice. Personnel Review **27**, 40–56 (1998). [1]

[10] Dimitriades, Z.S.: Empowerment in total quality: Designing and implementing effective employee decision-making strategies. Quality Management Journal **8**(2), 19–28 (2001)

[11] Ahearne M., M.J..R.A.: To empower or not to empower your sales force? an empirical examination of the influence of leadership empowerment behaviour on customer satisfaction and performance. Journal of Applied Psychology **90**(5), 945–955 (2005)

[12] Hales, D.: How far dare you go? Stakeholder **2**(4), 31–34 (2005)

[13] Silver, S., Randolph, W.A., Seibert, S.: Implementing and sustaining empowerment: Lessons learned from comparison of a for-profit and a nonprofit organization. Journal of Management Inquiry **15**(1), 47–58 (2006)

[14] Rudy, H., Jonathan, M.: Implementing empowerment through teams: the case of texaco's information technology division (1993). 158234 255-264

[15] Tsang, E., Gosling, T., Virginas, B., Voudouris, C., Owusu, G.: Retractable contract network for distributed scheduling. In: 2nd Multidisciplinary International Conference on Scheduling: Theory & Applications (MISTA), pp. 485–500. New York (2005)

[16] Tsang, E., Voudouris, C.: Fast local search and guided local search and their application to british telecom's workforce scheduling problem. Operations Research Letters, Elsevier Science Publishers, Amsterdam **20**(3), 119–127 (1997)

[17] Glover, F., Kochenberger, G.: Handbook of Metaheuristics (International Series in Operations Research & Management Science). Springer (2003)

[18] Muller, C., Magill, E., Smith, D.: Distributed genetic algorithms for resource allocation. Technical report, Strathclyde University (1993)

[19] Baker, S.: Applying simulated annealing to the workforce management problem. Technical report, British Telecom Laboratories (1993)

[20] Lever, J., Wallace, M., Richards, B.: Constraint logic programming for scheduling and planning. British Telecom Technology Journal **13**(No.1), 73–80 (1995)

[21] Yang, R.: Solving a workforce management problem with constraint programming. In: The 2nd International Conference on the Practical Application of Constraint Technology, pp. 373–387 (1996)

[22] Jackson, P.: Introduction to Expert Systems, 3rd edn edn. Addison Wesley Longman, Harlow, England (1999)

[23] Abraham, A.: Rule based expert systems. In: P.S. Thorn, Richard (eds.) Handbook for Measurement Systems Design, pp. 909–919. John Wiley and Sons Ltd., London (2005)

[24] Voudouris, C., Tsang, E.: Guided local search. In: F. Glover (ed.) Handbook of metaheuristics, pp. 185–218. Kluwer (2003)