MULTI-WORKDAY ERGONOMIC WORKFORCE SCHEDULING WITH PERSONAL AND TASK CONSTRAINT

BY

TARIT RATTANAMANEE

A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY (ENGINEERING AND TECHNOLOGY)
SIRINDHORN INTERNATIONAL INSTITUTE OF TECHNOLOGY
THAMMASAT UNIVERSITY
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Abstract

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by

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This dissertation deals with the Workforce Scheduling Problem (WSP) with a planning period that covers several workdays which is a multi-workday workforce scheduling problem (MW-WSP). An occupational ergonomic hazard in a workplace or workstation is considered. The safety law of industry states that workers must not be exposed to hazards beyond a daily permissible level. There are three commons approach to prevent or reduce occupational ergonomic hazards (e.g., engineering approach, administrative approach, personal protection equipment). The administrative approach is a popular tool which job rotation can be managed to increase the safety and decrease risk of exposure to excessive hazards. The complex personal and task constraints are considered. Workers are heterogeneous in terms of personal skill, ability, and preference. Workstations might have a multiple task and specific operation schedule in each workday. Multi-objectives are considered, the combination of three objectives; hazard exposure balancing, productivity, and satisfaction of workers; is introduced. Productivity, it is common-that management seeks a workforce scheduling solution with high productivity. When assigning a worker to a job that he/she can perform effectively, it is reasonable to expect high

performance from such worker-job assignment. In other words, the productivity directly relates to the person-job fit score. Workers with an unequal person-job fit score prefer a different task/team. When applying job rotation, a work schedule can affect the systems productivity and satisfaction of workers. Moreover, a multi-workday schedule can reduce fluctuation in the amount of hazard exposure among workers. Considering all the objectives, this research aim to provide not only more hazard protection to workers but also keep productivity and satisfaction high.

The mathematical models of the problem formulate are in the form of a mixed integer programming (MIP). The multi-objective approach called the LP-metric method is used to navigate to solutions are compatible to the decision maker's opinion. The optimal values from each aspect are set as target goal values for the LP-metric model. The optimization software IBM ILOG CPLEX V12.4.0 is used to solve the problem optimality. The WSP is a NP-hard problem, thus MW-WSP is more complex. When problem size increases, it is very difficult to find optimal solution with CPLEX. So, a genetic algorithm (GA) is employed to solve this problem. The permutation encoding is presented as the problem solution. The GA operation such as crossover is proposed with revised specific for the problem. The GA tool procedure is coded on the MATLAB script file (m-file).

From the numerical example, the LP-metric method return of a solution with respect to pre-set weigh and satisfied problem constraint. From the computation experiment, it is confirm that CPLEX could only guarantee the optimal solution for small size problems. The proposed GA could reach near optimal solution within reasonable computation time. Moreover, the application of multi-workday workforce scheduling was applied to vehicle routing and workers scheduling problems with manual material handling. An optimization and heuristic methods are proposed for problem solution approach.

Keywords: Multi-workday workforce scheduling, Ergonomics, LP-metric method, Multi-objective optimization, Genetic algorithm

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Introduction

1.1 Multi-workday Workforce Scheduling Problem

Workforce scheduling problem (WSP) is a famous combinatorial problem, dealing with the assigning of workers to perform a set of tasks over working time periods. Unlike the assignment problem, WSP assigns a worker or employee to perform any task under “time duration”. Workers are usually rotated among a set of tasks in each area. WSP is a complex problem due to a great number of constraints which need to be fulfilled. A few examples of constraints are industrial regulations, relevant workplace agreements, work condition rules, and personal preferences.

WSPs have benefited from extensive attention for many decades. Recently, they have extensively played an important role in many areas such as industrial or manufacturing factories, transportation systems, health care systems, service systems, emergency services, or even in universities. Depending upon each application, this sort of problem is denoted by the various names in the literatures and focuses on different objective considerations. The common objectives are found to be: (1) obtaining feasible work timetable under complex constraints, (2) minimizing the number of utilized workers, (3) minimizing the total cost, (4) maximizing total system productivity and performance, and (5) maximizing job satisfaction satisfying employee’ preferences. The general terms of workforce scheduling are: workforce scheduling, manpower scheduling, staff scheduling, labor scheduling, personal scheduling, employee timetabling, crew scheduling or rostering for transportation systems, nurse scheduling for health care systems, tour scheduling or agent scheduling for various service systems etc.

To obtain an efficient work schedule solution, a lot of factors need to be consider. A good work schedule solution should contribute advantages to both organization and employees. For the organization, total system productivity can be increased by suitable assignments. Employees trend to perform tasks with full capabilities particularly in their preferred tasks and/or partners with high morale. Employee turnover rate can be reduced resulting in decreased manpower management costs which gains more profits for the organization. The operation schedule, day-off or weekend-off constraint, and complex operator-task pairing are also the main restrictions. Due to those complex constraints, WSP is a difficult problem which can interface with real world problems.

WSP is complex because of the many restriction constraints and solution alternatives. The critical features of WSP are its computation behavior and flexibility to solve a wide range of problems that appear in practice. According to the complexity theory, in many cases, WSPs have been verified as an NP-hard problem. Thus, the computation time to solve problems grows exponentially when the problem size (decision variables) increases. Thus, WSP is definitely complicated when searching for the optimal solution within a reasonable computation time.

WSP is a combinatorial optimization problem. Various efficient solution approaches have been suggested in previous literatures. In summary, solution approaches in dealing with WSPs can be classified into 3 categories: optimization approach, heuristic approach, and metaheuristic approach.

WSPs are usually formulated as an integer programming model (IP), according mathematical programming in optimization approach. Set covering or partitioning model and its variations are alternative formulations. They can be solved by using an exact algorithm such as the branch-and-bound method, branch-and-price, branch-and-cut, and Lagrangian heuristic. Moreover, WSP can be solved by other efficient methods in the optimization approach such as goal programming, network model, multi-commodity network flow, dynamic programming, matching model, decomposition model, or combinatorial models among those methods.

The heuristic algorithm or approximation techniques are an alternative solution approach. The strategy is to determine a good solution or near optimal solutions for larger size problems by consuming reasonable calculation time. However, the step by step process of each algorithm needs to be clarified and well designed for each particular problem. Heuristic procedures generally do not work well if the problem is highly complex constrained. The solution may fall into a local optimal solution and may not find the near optimal solution. Examples of heuristic methods applied to workforce scheduling are the swap and interchange based neighborhood search heuristics which are commonly utilized in airline crew rostering problems, local search methods utilized in bus driver scheduling problems, and other proposed algorithms. Unlike the exact algorithm, heuristics alogirthm cannot guarantee the optmality of solution.

The metaheuristic approach has attracted attention from researchers for over the last few decades. Typically, metaheuristic is used to solve problems that cannot be solved by traditional heuristics. This approach can escape from local optimal to find global optimal by a specific mechanism (natural or non-natural inspire). On the other hand, they can classify as evolutionary or non-evolutionary mechanism. Modern metaheuristics have been applied to scheduling problems such as simulated annealing (SA), ant colony optimization (ACO), tabu search (TS), particle swarm optimization (PSO), and genetic algorithm (GA). SA is usually founded in airline crew scheduling, train crew rostering, and cyclic staff scheduling problems; TS in nurse rostering, air crew scheduling, audit scheduling, and bus driver scheduling; and GA in industrial workforce scheduling, nurse scheduling, and bus driver scheduling. Among those metaheuristics, GA is found to be most utilized in solving scheduling problems. Only a few combinatorial algorithms among those metaheuristics are founded.

Three main considerations of workforce scheduling problem are addressed for effective work schedule solutions. They are: (1) ergonomic-based workforce scheduling, (2) productivity-based workforce scheduling, and (3) job satisfaction-based workforce scheduling. Moreover, workforce scheduling problems are addressed for work schedule duration. They are: (1) single-working day workforce scheduling, (2) multi-working day workforce scheduling.

Occupation injuries can occur in many workplaces environment because of exposure to ergonomics hazard or other factors. Ergonomic consideration is one essential factor which needs to be covered. There are many types of tasks that are unavoidable for workers to receive hazard exposure when they perform tasks. For example, the task that involves lifting heavy workloads, workload with energy expenditure, doing repetitive work, and performing in hazardous environments i.e., loud noise, high temperature, and radiation or chemical zone. Excessive hazard exposure beyond the permissible limit can cause many injuries or illnesses. For example, musculoskeletal disorder, cumulative trauma disorder, permanent hearing loss, heat stress, chemical burn, radiation burn, which can lead to death. Thus, ergonomic-based workforce scheduling becomes an important issue which has lead to many researches paying attention in this aspect. According to the safety regulation issued by the U.S. Occupational Safety and Health Administration (OSHA), daily hazard exposure of workers must not exceed the permissible limit. OSHA recommended three hierarchical approaches to prevent occupation ergonomics hazard, namely, engineering approach, administrative approach, and the use of personal protection equipment. However, they are not cost effective and many times seem to be limited in practice. An administrative control strategy, job rotation could be practically implemented to solve this problem.

Total system productivity is one of definitions of effective workforce schedule solutions. Productivity-based workforce scheduling benefits an organization by obtaining higher profits via efficient resource management. Achieving high total system productivity can be done by either increasing production rate or decreasing various losses. With no significance on addition cost, many organizations select this way to reduce many types of loss. Utilizing manpower in effective ways is mostly considered. For example, minimum workforce size, person-job fit strategy. However, there are only a few previous literatures focusing on the high total productivity in the area of workforce scheduling. As an effect of job rotation, the total system productivity can be reduced because a few workers might be rotated who are incompetent or do not fit the tasks.

Worker job satisfaction provides advantages to both workers and organization. It is the fact that workers who perform their preferred tasks and/or with preferred partners tend to do spotless work. Satisfaction in the workplace environment can lead to reduced turnover rate, high morale, resulting in a lower human resourcing management cost. Nowadays, employee’s preference becomes a factor when constructing a work schedule. They include the terms of workers’ preferred days-off, shift-start and/or shift-end period, or priority job preference.

For work schedule duration, a single-workday workforce scheduling is a multi-period schedule which focuses on assigning workers to tasks or shifts in one day. This can be separated into multiple periods for assigning or job rotation. For a multi-workday workforce scheduling problem, this problem setting is applied in various fields, the problem focuses on assigning employees to the shift or task in a multiple workday planning horizon (e.g. weekly, monthly).

1.2 Problem Statement

To construct an effective WSP solution, three main considerations are required to determine the combination, e.g., ergonomic issue, productivity aspect (e.g., person-job fit), and workers' satisfaction. By considering these three aspects, many contributions go to both workers and organization. Workers' hazard exposures are controlled resulting in less occupation injury problems. Turnover rate is significantly reduced due to the workers' job satisfactions in both task and co-worker preferences. An organization can reduce much workforce management cost i.e., expense for medical treatment and training tuition fee for new coming workers, compensation payment, and indemnity.

Because of conflictions among those approaches, multi criteria analysis (MCA) is required for suitable benefit tradeoff with multi-objective optimization tools. To protect manpower from exceeding hazard exposure permissible limit, a few workers might be assigned to the tasks that they are incompetent or do not fit for a few work periods. As a result, total system productivity can be reduced. Worker preferences of tasks and partners, in the same fashion, sometime have to be violated as soft constraint. However, it should be satisfied as much as possible. Unfortunately, there are only a few researches that include those three aspects in a combination.

For ergonomics hazard exposure reduction, an effective way to overcome this serious problem is by implementing the "job rotation". Job rotation is an administrative approach suggested by the U.S. Occupational Safety and Health Administration (OSHA). It can help to reduce the amount of hazard to the worker by rotating the workers among the tasks periodically. So, the physiological effect from the hazardous jobs can be shared by many workers instead of being accumulated by only one worker. It's obvious that job rotation can be suitably implemented when constructing work-schedules. Therefore, the concept of job rotation is taken into account when combining the ergonomic consideration with workforce scheduling. It is important that the total hazard exposure must to be kept under the permissible limit along working time in every workday. Thus, the job rotation should be considered in more details such as dividing a workday into work periods (i.e., 2 hours/periods) so that worker can be assigned to different tasks (preferred in different location) in each work period within a day. Moreover, the total hazard exposures of each worker need to be determined in quantitative amounts so as to be obvious in evaluating, monitoring, and controlling.

However, effective job rotation is known to be difficult in implementation because there are many complex constraints and limitations which are not included in previous research models. In real workplaces in any workstation, hazard exposure can be classified as uniform or non-uniform hazard types from the different sources of hazard. The uniform hazard exposure can affect all workers with equal hazard level, i.e., industrial noise. For the non-uniform hazard exposure, each worker performs a different task in the workstation which might receive an unequal hazard exposure level and capacities to withstand those hazard. This comes from the fact that workers are non-identical. Apart from the different preferred tasks and partners, they have different skill levels even when performing the same tasks based on training and back ground experience. In the point of workstation' characteristics, numerous workstation require more than one task for operation. Both single and multiple task operation should be included. And the last main constraint is that the workstation could be halted in a few work periods of any workday according to its operation schedule. It's necessary to consider those worker and task constraints when constructing efficient and realistic approached dealing with WSP.

In summary, previous workforce scheduling research still misses out on a few essential considerations. The limitations of previous research can be classified into 4 main points which are:

1. <u>Lacking consideration of ergonomic issues, productivity aspect, and workers' job satisfaction</u>: Even though WSPs have been extensively studied for a long time, there are just a few numbers of researches focusing on these important aspects.

2. <u>Focusing on only one objective</u>: Most of the previous researches pay attention to only one particular objective, do not consider problem in combination. The system can be improved by taking more than one aspect into consideration e.g., ergonomic issue, productivity aspect, and workers' satisfaction. Simultaneous achievement is needed in real circumstances.

3. Rotating tasks on workday horizon: Job rotation consideration of previous works was mostly done under a workday shift change. Workers' hazard exposure cannot be effectively managed. It may occurred that workers' hazard exposure in a workday are over the limit resulting in health problems. Moreover, the total hazard exposure of workers has not been evaluated in quantitative amounts.

4. Focusing on a single workday planning horizon: Past research of workforce scheduling considered ergonomic hazard exposure studies were only concerned with finding either optimal or near-optimal solutions for one day. This is perhaps based on an assumption that the workers' work schedules will be the same as long as job requirement do not change. These fixed work schedules can lead to unfair worker-task assignments for a few workers since they could be assigned to more hazardous tasks than other workers.

1.3 Research Objectives

This research is conducted to deal with multi-workday workforce scheduling problem in a more effective way. The limitations of previous studies will be resolved focusing on five main points. In conclusion, the new model of workforce scheduling in this research includes:

1. Ergonomic, productivity, and workers' satisfaction considerations: To fulfill the research area in WSP, the ergonomic, productivity, and workers' satisfaction are taken into account. This research could be an early WS model that covers all of those 3 aspects together.

2. Multi-objective multi-workday workforce scheduling consideration: Those three aspects are considered in combination. The best suitable tradeoff solutions are determined instead of achieving only one objective. The objectives are set in three priority goals which are:

- minimizing the ergonomics hazard exposure variation (among worker),
- maximizing the total system productivity by maximize of person-job fit score, and
- maximizing workers' satisfactions in both task and team assignment preferences.

3. Daily job rotation under quantitative approach: A workday is divided into equal work periods. Workers' hazard exposure can be effectively controlled

under the permissible limit by rotating workers to other suitable tasks in the end of work period within a day. The total hazard exposures of workers are evaluated in quantitative amounts so as to be obvious in monitoring and controlling.

4. Realistic constraints in hazard exposure and worker-task requirements: two types of single-limit hazard are considered. Complex worker and task constraints are covered. Worker constraints are: limited work ability, different person-job fit level, and team preference and task preference. Task constraints are: single or multiple task operation in a workstation and workstation operation schedule.

5. Multi-workday planning period: Unlike previous studies that focused on finding solution for one day. A Multi-work day planning period intends to assign worker to tasks in multi-day schedule simultaneously so workers can be assigned fairly to a one day planning period work schedule.

The multi-workday workforce scheduling problem in this research is conducted with three objectives:

1. To develop a mathematical model for multi-objective multi-workday workforce scheduling problems with person-job fit, job preference and team assignment consideration under one single-limit hazards and complex worker-task constraints.

2. To propose a genetic algorithm approach for multi-objective multi-workday workforce scheduling problems with person-job fit, job preference and team assignment consideration under one single-limit hazards and complex worker-task constraints.

3. To conduct a computation experiment for multi-objective multi-workday workforce scheduling problems.

1.4 Dissertation Overview

This dissertation consists of seven chapters which are organized as follows:

Chapter 1 provides an introduction of the multi-workday workforce scheduling problem along with its solution approaches. The workforce scheduling problem generally is classified as an NP-hard problem. The problem statement is stated. The ergonomic consideration in form of job rotation is taken into account. The conflict objectives needed to be resolved. The multi-workday planning period is considered. Realistic assumptions in both worker and workstation factors are included. The research objectives are then summarized.

Chapter 2 contains the literature review. Related articles are reviewed and categorized into four main topics, namely, the multi-workday workforce scheduling problem and its variants, quantitative approaches to multi-workday workforce scheduling, focus of multi-workday workforce scheduling.

Chapter 3 presents a mathematical model to optimize the multi-objective multi-workday workforce scheduling problem. Firstly, the problem description is stated. Six assumptions and five conditions are defined. A mathematical model is presented and explained in detail.

Chapter 4 presents a genetic algorithm (GA) for the proposed problem. The concepts of GA used in this research are provided. Chromosomes are represented using the integer permutation. The operation of GA is also presented.

Chapter 5 provides a numerical example to determine optimization, and GA approaches. First, the problem description is clarified. Then, two mentioned approaches are implemented. Results are shown for comparison.

In Chapter 6, a computation experiment is conducted with six test problems. The solutions of each problem in each approach are determined and compared.

Chapter 7 is the conclusion of the research. This chapter includes a summary and the key contributions of the research. The recommendations for further studies are also given.

Appendix A presents application of multi-workday workforce scheduling problems in vehicle routing problem with manual materials handling (VRPMMH). The new problem called multi-workday VRP (MW-VRP). First, the problem description is clarified. Then, the mathematical model and heuristic procedure approaches are implemented. Numerical Results are shown for comparison. The computation experiment is examined.

Chapter 2
Literature Review

This chapter introduces multi-workday workforce scheduling problems and its variants in related application areas, namely, transportation system, health care system, and service system. Complex and difficulties of workforce scheduling problem are stated. Quantitative approaches included three categories e.g., optimization, heuristic, and metaheuristic approach are reviewed. Focus of multi-workday workforce scheduling in ergonomics, productivity, and job satisfactions are presented.

2.1 Multi-workday Workforce Scheduling Problem and Its Variants

Assigning resources to a set of tasks over given time periods is a scheduling problem (SP). SP is a common problem faced in organizations. However, the resources and tasks can be in many different forms. The resources might be machines in a workshop, runways at an airport, crews at a construction site, processing units in a computing environment, operating rooms in a hospital, and vehicles in transportation agency; whereas, the tasks might be operations in a production process, take-offs and landings at an airport, stages in a construction project, executions of computer programs etc. (Michael Pinedo, 2008). At the beginning of SP study, only applications in machine scheduling and project planning attracted attentions were researched. In machine scheduling, a large number of specific scheduling situations depending on the machine environment and the job characteristics have been considered. In project planning, focus is on the investigation scheduling situations with precedence constraints between activities assuming that sufficient resources are available to perform the activities. But later on, scarce resources were taken into account leading to so-called resource-constrained project scheduling problems (RCPSP).

Workforce scheduling problem (WSP), as oppose to RCPSP, determined how to assign workers to perform tasks over a set of working periods. Resources in this case are defined as the manpower. Unlike the assignment problem, WSP assigns workers or operator to attend any task under “time duration”. Workers usually are found to be rotated to other tasks in each day (not constantly assigned as in assignment problem). WSP is a complex problem due to a great number of constraints needing to be fulfilled. The examples of constraints are industrial regulations, relevant workplace agreements, and personal preferences.

Researchers have been interested in WSP for over half a century. The trendsetter of workforce scheduling can be traced back to Edie's work on traffic delays at toll booths (Edie, 1954). Nowadays, workforce scheduling extensively plays an important role in many areas such as industrial factories, transportation systems, health care systems, service systems, emergency services, and universities. Depending on the application areas, WSP is called by various names and focuses on different objective considerations. The common objectives are found to be: obtaining feasible work timetable under complex constraints, minimizing the number of utilized workers (finding a set of assignments that required the smallest number of workers to complete entire tasks), minimizing the total operation cost or investment (finding a set of assignments that leads to the lowest cost while all tasks can be accomplished), maximizing total system productivity or performance (focusing on the highest productivity performance), and maximizing job satisfaction (satisfying operators' preferences).

WSP is sometimes called as manpower or a labor scheduling problem in industry. The number of utilized workers is mostly the consideration to be minimized. Hung (1994) dealt with a multiple-shift workforce scheduling problem. This research aimed to minimize workforce size subject to satisfying staffing requirements on weekdays and weekends, and work rules relating to shift changes, off-days, and off-weekends. Other examples are: Alfares (2003) and Lagodimos and Leopoulos (2000). The total cost (Billionnet, 1999), labor cost (Elshafei & Alfares, 2008), productivity (Arroyo & Armentano, 2005; Chang et al., 2008; Chang et al., 2007; Ip et al., 2000; Sha & Lin, 2010; Yagmahan & Yenisey, 2010), and job satisfaction (Jaturanonda & Nanthavanij, 2005; Peters & Zelewski, 2007) are also determined. Transportation system (i.e., bus and rail transit, truck and rail freight transport, and freight and passenger air transportation) is a large application of WSP. Usually, it is called as crew scheduling or rostering. In this area, the objective is mainly focused on the total cost (dos Santos & Mateus, 2009; Souai & Teghem, 2009; Stolletz, 2010), and productivity. The high total productivity can be determined in many forms such as minimum idle shifts (Chu, 2007), maximum number of assigned tasks (Dohn et al., 2009), and maximum service levels (Ho & Leung, 2010). The minimum number of workers was found to be an objective in only a few researches in this area, for example, research of Yang et al. (2003) and Yang et al. (2004). Since airline scheduling usually consists of two sequential sub-problems: airline crew pairing problem (CPP) and airline crew assignment/rostering problem (CAP/ CRP), a few researches determined feasible schedule solutions via integrated approaches. The examples are research by Guo et al. (2006) and Mesquita and Paias (2008).

In the health care system, the problem is defined in term of nurse scheduling. The problems basically restricted under a large number of constraints and involves many aspect considerations (Azaiez & Al Sharif, 2005; Maenhout & Vanhoucke, 2013; Mobasher et al., 2011; Purnomo & Bard, 2007). Multi-objectives are usually considered, especially combining factors in productivity aspect. The multi-objective consideration under many restricted constraints proposed in many literatures (Aickelin & Dowsland, 2004; Berrada, Ferland, & Michelon, 1996; Millar & Kiragu, 1998; Trivedi, 1981; Tsai & Li, 2009; Valouxis & Housos, 2000). The total cost is another objective focused in this application (Abrahams & Ragsdale, 2012; Brunner & Edenharter, 2011; Maenhout & Vanhoucke, 2010). Tour scheduling or agent scheduling is normally called WSP in application of service systems (i.e., center, hotels, restaurants, police, ambulance, fire brigade, retail sector (Kabak et al., 2008), and postal service (Bard et al., 2003). Minimizing the total cost is the most popular objective in this application (Alfares, 1998; Avramidis et al., 2010; Bard et al., 2003; Kabak et al., 2008; Topaloglu & Ozkarahan, 2003). Ezik at al. (2001) formulated the integer programming model to determine a set of tours to meet the demand of agent service while minimizing the combination of labor cost and unsatisfied demand. Another objective is to maximize total productivity, for example, in terms of minimizing the number of startups and the number of machines used per operation (Zhang & Bard, 2006).

The WSP has a different schedule duration or planning period. A multi-period workforce scheduling, which intends to assign workers to tasks or shifts in single day planning horizon separated into multiple periods. According to Sabar et al.

(2008) studied a multi-period scheduling of worker in large assembly line, the mathematical model was developed, competencies and preference of workers were considered. A work period was set equal to the line's preset takt time between two product units. The objective is to satisfied personnel requirements at each station in each period during the planning horizon while minimizing cost and dissatisfaction. The commercial optimization software ILOG CPLEX is used to find optimal solution. Bhadury and Radovilsky (2006) proposed an assignment model with a multi-period setting. The periods of assignment can be defined arbitrary. The bi-objective optimization models are formulated for two objectives, the usual objective of minimizing the total cost of assignment. Additionally, the objective are also considered to minimize boredom felt by employees due to continued repetition of the same task over consecutive periods.

A multi-workday workforce scheduling problem is applied in various fields, the problem focuses on assigning employees to the shift or task in multiple workday planning horizon (e.g., weekly, monthly). The manpower scheduling in an manufacturing environment was studied by Pan et al. (2010). The planning horizon defined as multi-day schedule. The objective is to minimize total payment on employees. The mathematical formulation was developed as mixed integer programming, a two stage heuristic algorithm was proposed. Musliu et al. (2002) proposed an algorithm for cyclic or rotating general workforce schedules for multiple days. Workers will start at different beginning periods. An integer programming model and a two-stage solution method for flexible 4-day workweek scheduling problem with weekend work frequency constraints was proposed by Alfares (2003). The employees were given 3 days off per week, out of which either 2 or 3 must be consecutive. The objective is to determine the minimum workforce size. Additionally, he also developed workforce scheduling under the (14, 21) days-off timetable. In planning horizon, each worker is given 14 successive workdays and 7 successive off days. Demand of manpower required varying on each day of the week. The primary goal was to minimize number of workers (Alfares, 2002). The monthly tour scheduling models considered mixed skills and weekend off requirements were studied by Rong (2010). Bard et al. (2014) studied the monthly scheduling of residents in primary care clinics with the objective of maximizing the number of interns and residents for healthcare service management. A weekly schedules for therapists who treat patients with fixed appointment times at various healthcare facilities was proposed by Bard et al. (2014).

For the general WSP in other application areas, they might be called as staff scheduling, personal scheduling, or employee timetabling. A few research studies were conducted focusing on feasible work schedule under complex constraints. For example, Lau (1996) set a main objective to construct an assignment of shifts to workers subject to manpower demands and shift-change constraints, while Kim et al. (2004) attempted to assign operators to time slots of equipment usage under a number of constraints, which are: restrictions on the minimum workforce assignment to each time slot, the maximum total operating time per operator per shift, the minimum and maximum consecutive operating times for an operator, types of equipment that can be assigned to each operator, and the available time slots for each operator or piece of equipment. Nowadays, ergonomic consideration has become more interesting to researchers. According to the U.S. Occupational Safety and Health Administration (OSHA), ergonomics is the science of fitting workplace conditions and job demands to the capabilities of the working population. Indeed, the effective ergonomics implementations assure the high productivity, avoidance of illness and injury risks, and increased satisfaction among the workforce. Through regulation and its own obvious advantages, ergonomics has gained visibility in much of industry and other areas in recent years. For details about ergonomic consideration in workforce scheduling, see section 2.3.1.

2.2 Quantitative Approach to Multi-workday Workforce Scheduling

WSP is a combinatorial optimization problem which is known as a complex and difficult problem. For more than five decades, considerable effort has been devoted to tackling the problem. Various efficient solution approaches have been suggested in previous literatures. In general, the unique characteristics of different organizations means that specific mathematical models and algorithms must be developed in different areas of application (Ernst et al., 2004). However, main solution approaches in dealing with WSPs can be classified into 3 categories: optimization approach, heuristic approach, and metaheuristic approach.

2.2.1 Optimization approach

Mathematical Optimization, so called as Numerical Optimization or Mathematical Programming, is defined as the science of determining the “best” solutions from lots of schemes to certain mathematically defined problems, which are often models of physical reality. The history of the optimization started at the end of the 1940s, when the simplex method to solve the special class of linear programming problems was developed by George Bernard Dantzig (Diwekar, 2008).

In the optimization approach, WSPs are generally formulated as (binary/mixed) integer linear programing (Bard et al., 2003; Billionnet, 1999; Gomar et al., 2002; Yang et al., 2003). The comparisons among those methods are also determined. Rong (2010) dealt with the monthly tour scheduling problem with mixed skills considering the weekend off requirements. The objective was to obtain the most economical mix of types of workers satisfying the patterns of demands for the workers and desired work characteristics. Two model formulations are developed based on implicit programming techniques – general integer programming (GIP) with assigning lunch break hours to the workers based on the worker types and binary integer programming (BIP) with assigning lunch break hours explicitly to the individual workers. Based on the numerical tests and the results, it is shown that even though the problem size of the BIP formulation is larger, the BIP formulation performs better than the GIP formulation in terms of lunch break assignment, solution quality, and solution efficiency. The model structure, instead of the problem size, is stated to become a dominant factor to affect the solution efficiency.

Algorithms based on an optimization approach generally achieve the lowest cost solutions. However, it is more limiting in what constraints and objectives can be expressed easily. Characteristics of WSP can be formulated as a set covering/partitioning model or its variations which can be solved by using an exact or heuristic algorithm such as branch-and-bound method, branch-and-price, branch-and-cut, and Lagrangian heuristics. Topaloglu and Ozkarahan (2003) considered weekly tour schedules with fluctuating customer demand. They stated that tour-scheduling problem has been traditionally formulated by the set-covering approach. However, when problem becomes larger with many decision variables (due to different work days and different shift and break start times in a workweek), set-covering formulation might be impractical to formulate problems. Thus, they proposed an implicit integer-programming approach to facilitate the formulation of optimal tour-scheduling problem compared to the set-covering approach. The results indicated that the implicit form of the model is outstanding in requiring fewer integer variables than the set-covering approach.

Moreover, WSP can be solved by other efficient methods in the optimization approach such as goal programming (Chu, 2007; Jaturanonda & Nanthavanij, 2005; Li et al., 2012; Topaloglu, 2006; Trivedi, 1981), stochastic programming (in case of stochastic demand), network model (Millar & Kiragu, 1998) multi-commodity network flow, dynamic programming, matching model, decomposition model, or combinatorial models among those methods (Ernst et al., 2004). Peters and Zelewski (2007) and Mathirajan and Ramanathan (2007) utilized goal programming (GP) to solve their problems in both preemptive and non-preemptive considerations. Mathirajan and Ramanathan (2007) studied the problem of scheduling the tour of a marketing executive to visit a number of customers in a given period. The restrictions are formulated as soft and hard constraints to GP. Three objectives are set to minimize the sum of deviational variables corresponding to three sets of soft constraints. The results indicated that non-preemptive version is outstanding in comsuming less computation time (with the same solution quality); however, an appropiate weighting scheme needs to be assigned. Peters and Zelewski (2007) developed a model for the assignment of employees to workplaces, in which determining in worker competences and preferences. In this research, relative importances of three objectives are employed by using the relative measurement mode of the analytic hierarchy process (AHP). Mesquita and Paias (2008) dealt with integrated vehicle and crew scheduling problem (VCSP). The problem is described as an integer linear programming formulation combining a multi-commodity network flow model with a set partitioning/covering model. Two different mathematical models were proposed, namely, SP-VCSP (an original partitioning model) and SPC-VCSP (a mixed covering/partitioning model). The methodology to handle models is divided to 4 main steps: (1) defining the set of tasks, (2) constructing an initial set of duties, (3) solving the linear programming relaxation of the models using a column generation scheme, and (4) using branch-and-bound techniques to guarantee the integer optimal solution.

The optimization takes advantage of achieving the guaranteed highest or lowest particular aspects but for the large-sized problem it seems to be limited. Since WSP is classified as an NP-hard problem, the number of variables grows exponentially when the problem size increases (Gartner et al., 2001; Lau, 1996b). In recent years, column generation is brought to this issue especially to resolve such a situation. Briefly, problems are decomposed to a master problem and one or more subproblems. Using dual prices provided by the master problem, the subproblems generate new columns to be added into the master problem. Then, instead of solving the problem with the whole set of columns, it is solved incrementally each time with new columns added. The problem can be solved without enumerating all the columns, and the optimality may be proved even without knowing the non-generated columns. Each part of formulation can be modified by combining other techniques such as heuristic or genetic algorithm so as to improve the efficiency of algorithm. dos Santos and Mateus (2009) dealt with crew scheduling problems by formulating the problem as set partitioning (SPP) and solving using the column generation technique. Interestingly, a genetic algorithm can be implemented to speed up the generation of new columns while the last column is generated by an exact method (e.g., ILP) to ensure the optimality. Brunner and Edenharter (2011) implemented column generation-based heuristic to a mixed-integer problem of staff scheduling with different experience levels. Unlike traditional column generation, final LP solution is transformed to an IP solution by solving the master problem as IP after column generation terminate. Later, the IP problem is solved to optimality. For another example, see (Dohn et al., 2009).

2.2.2 Heuristic approach

Heuristic procedures/methods are any technique that do not guarantee or promise the optimal solutions but attempt to provide a ‘good’ and sometimes ‘near optimal’ solution in a minimal amount of time (Bazargan, 2010; Sinnen, 2007). As a logical consequence of the NP-completeness of scheduling, the scientific community has been eager to investigate efficient scheduling algorithms based on heuristics or approximation techniques to produce near optimal solutions in larger size problems.

Step by step process of each algorithm needs to be clarified and well designed for a particular problem. Heuristic procedures generally don't work well if the problem is highly constrained unless the constraints can be built directly into the heuristic (Rayward-Smith et al., 1996). However, many heuristic algorithms are found to be efficient in both solution time and solution quality.

Examples of heuristic methods applied to workforce scheduling are the swap and interchange based neighborhood search heuristics which are commonly utilized in airline crew rostering problems, and local search methods utilized in bus driver scheduling problems. Lagodimos and Leopoulos (2000) determined a manpower shift planning problem to minimize workforce size in each workday shift. Two greedy heuristic algorithms are introduced for tackling single and multi-shift problems. The algorithms are implemented in VBA and compared to the results of solving ILP from LINGO. See details in the paper by (Musliu et al., 2002). For other examples, see Hung (1994), Narasimhan (1997), and Castillo et al., (2009). Yan et al. (2004) utilized both optimization and heuristic method to deal with airline short-term maintenance manpower supply planning. The manpower is considered as unequal-work skills. Technicians are divided by multiple types of aircraft maintenance certificates. Three flexible management strategies and the related operating constraints are included in the models. Eight different flexible strategic models (associated with different strategy combinations) are evaluated. At first, the models are formulated as mixed integer programs and solved by using CPLEX. Due to the huge problem size in real applications, solution algorithm procedure was proposed which included 6 steps. A case study was implemented using the operating data from a leading Taiwan airline.

The combinatorial approach among optimization and heuristic procedure was also founded. Lau (1996a) proposed combinatorial algorithms for the change shift assignment problem (CSAP). His model was formed as a fixed-charge network. A feasible schedule can be obtained by finding disjoint paths in the network. He stated that if the schedule is tableau-shaped, the disjoint paths can be derived from an optimal path cover, which can be found by a polynomial-time algorithm and, if all constraints are monotonic, CSAP may be solved by a pseudo-polynomial backtracking algorithm. Musliu et al. (2002) proposed a framework to solve the problem of assigning days-off and shifts to employees. The combination of constraint satisfaction and problem-oriented intelligent backtracking algorithms were presented. Constraint satisfaction is split up into four steps so that the search space is reduced for each step, which provided the possibility of using backtracking algorithms. The four steps were: (1) choosing a set of lengths of work blocks, (2) choosing a particular sequence of work and blocks of days-off, (3) enumerating possible shift sequences for the chosen work blocks subject to shift change constraints and bounds on sequences of shifts, and (4) assignment of sequences of shifts to blocks of work while fulfilling staffing requirements. The presented method was implemented to addresses the previous research problems and compared results. The results showed that solutions can be found much faster than the previous one.

2.2.3 Metaheuristic approach

Metaheuristic is a set of concepts developed from heuristic methods. As a general algorithmic framework, it can be adapted to any specific problem by relatively few modifications. However, an effective metaheuristic needs to provide a balance between the exploitation of the accumulated search experience and the exploration of the search space to identify regions with high quality solution (Osman & Laporte, 1996; Stützle, 1998). Since a heuristic procedure is especially proposed for a particular problem, a new algorithm needs to be developed or at least modified to apply to other applications. The metaheuristic approach has attracted attention from researchers over last few decades. Typically, metaheuristic is used to solve problems that cannot be solved by traditional heuristics. The problems are either difficult in their own right or practical real-world instances making them intractable for solution –combinatorial optimization problem i.e., WSP.

Modern metaheuristics have been applied to scheduling problems for over a decade, examples are, simulated annealing (SA) (Loukil et al., 2005; Seçkiner & Kurt, 2007), ant colony optimization (ACO) (Seçkiner & Kurt, 2008;Yagmahan & Yenisey, 2010), tabu search (TS) (Musliu, 2006), particle swarm optimization (PSO) (Lian, 2010), and genetic algorithm (GA). The metaheuristics applied to areas of workforce scheduling problem. For example, SA is usually applied to airline crew scheduling, train crew rostering, and cyclic staff scheduling problems. TS is applied to nurse rostering, air crew scheduling, audit scheduling, and bus driver scheduling.

GA is applied to industrial workforce scheduling, nurse scheduling, and bus driver scheduling. Among those metaheurstics, GA is found to be the most utilized when solving scheduling problems i.e., Chang et al. (2007), Morz and Musliu (2004) and Cai and Li (2000). Tsai and Li (2009) developed a two-stage mathematical model for nurse scheduling problems. The nurse work and vacation schedules are arranged in the first stage. After that, the nurse roster schedule are arranged in the next step. GA is utilized after each stage in order to solve the optimal schedules and check for any constraint violations e.g., government regulations, hospital management requirements, and the scheduling fairness. Ho and Leung (2010) compared two model formulations – tabu search heuristic and a simulated annealing heuristic approach in solving a manpower scheduling problem for airline catering. From the computational experiment, the tabu search approach outperforms the simulated annealing approach for the research problem. Aickelin and Dowsland (2004) solved a manpower scheduling problem in a hospital using GA with an indirect coding based on permutations and a heuristic decoder. The proposed method was called an indirect GA. The individuals in the population do not represent direct encodings of solutions. Instead, solutions are obtained via separate decoder heuristics that build solutions from permutations of the list of available nurses using the constraints as guides. Penalty functions might still be required if the decoder fails to find a feasible solution. Three different decoders with varying levels of intelligence and four well-known crossover operators are determined. Results indicated that indirect GA can find high quality solutions in both faster and more flexibly than tabu search approach published in that period of time. Only a few combinatorial algorithms among those methods in metaheuristic approach are founded such as hybrid TS algorithm, which combines SA and GA (Ernst et al., 2004) and hybrid GA combining local searches with genetic population management techniques (Valls et al., 2009). Xia and Wu (2005) proposed hybridization approach of PSO and SA for multi-objective flexible job-shop scheduling problems. The objectives were to minimize the makespan, total workload of machines, and workload of the critical machine. PSO is the main part of hybrid search process. It is utilized to assign operations on machines to be initial solution to SA. While SA acts as a sub-algorithm to schedule operations on each machine and compute particle's fitness value for PSO. Then, PSO uses the solutions evaluated by SA to continue evolution.

The combinatorial methods among optimization, heuristic and metaheuristic approach were also considered. Valouxis and Housos (2000) considered monthly work shift and rest assignment of hospital nursing personnel problems. A hybrid method that combined integer linear programming and tabu search were presented. Köksalan and Burak Keha (2003) used GA to improve the solution obtained from a prior heuristic procedure. Initial heuristics were utilized to include good solutions into the initial population of GA. They developed an efficient procedure that uses the probability of each chromosome for being a parent. Local searches were utilized in their GA. Remde et al., (2007) studied a complex real-world workforce scheduling problem. They split the problem into smaller parts and solved each part using an exhaustive search. Reduced variable neighbourhood search (rVNS) and hyperheuristic approaches are utilized to decide which sub problems are tackled in order at each stage of solution process. Parallelization was used to perform nearly one CPU-year of experiments. The results showed that the new methods could produce results with better fit than the genetic algorithm in less time and they were far superior to any of their component techniques. Chitra et al. (2011) solved task scheduling problems by minimizing the makespan and maximizing the reliability using hybrid evolutionary multiobjective optimization algorithms. Li et al. (2012) presented a hybrid approach comprising goal programming and meta-heuristic methods for the multi-objective optimization of nurse scheduling. The algorithm was called the falling tide algorithm. Goal programming model is employed to produce an ideal objective-value vector and an initial solution as its inputs. The ideal objective-value vector acts as a reference point in a compromise programming based function to evaluate the quality of result solutions more efficiently, while the initial solution acts as a good seed for the falling tide algorithm to speed up the convergence.

The variants of other techniques implemented to WSP are illustrated. Constraint satisfaction technique is utilized in formulation a problem of port container terminals by Kim et al. (2004). The schedule must satisfy constraints on operating time, rest time, and operator preferences. Avramidis et al. (2010) proposed simulation-based algorithms combining simulation with integer or linear programming to solve the agent scheduling problem in a multi-skill call center. The objective was to minimize the total costs of agents under constraints on the expected service level per call type, per period, and aggregated. Bagatourova and Mallya (2004) presented a simulation model and a heuristic algorithm using simulation to estimate objective function for workforce scheduling in a highly variable environment. The two stage model/algorithm is used in Alfares (1998) and Kabak et al. (2008). Topaloglu and Seyda (2006) studied a multi-objective programming model for scheduling emergency medicine residents. The problem underlies on a large number of rules related to various aspects i.e., limits on the number of consecutive work hours, number of day and night shifts that should be worked by each resident, resident staffing requirements according to seniority levels for the day and night shifts, restrictions on the number of consecutive day and night shifts assigned, vacation periods, weekend off requests, and fair distribution of responsibilities among the residents. Goal programming (GP) model is formulated with both hard and soft constraints for a monthly planning horizon. Unlike most researches, analytical hierarchy process (AHP) can compute relative importance values of the soft constraints which can be used as coefficients of the deviations from the soft constraints in the objective function.

2.3 Focuses of Multi-workday Workforce Scheduling

In this dissertation, three main considerations of workforce scheduling problem are addressed: (1) ergonomics and safety, (2) productivity, and (3) other considerations. Details and literature reviews in each topic are provided as follows.

2.3.1 Ergonomics and safety

Many assigned tasks involve occupational hazards. It is unavoidable for workers to receive hazard exposure from their workplaces when performing routine tasks. The hazard can be emitted from many different ways: for example, lifting too much workload, doing repetitive tasks in improper postures, receiving a loud noise level from machine operations and vibrations, working in high temperature environment for long periods, and exposing to chemical or radiation without suitable protection equipment. Exposing to hazards over the permissible limit can cause injuries or illness such as musculoskeletal disorder, cumulative trauma disorder, permanent hearing loss, heat stress, chemical burn, radiation burn, or even lead to death. Workers with occupational problems cost organizations a lot in health support service, health care treatment cost, and high turnover rate. Workers with full experiences could be lost resulting in a reduction of the total system productivity.

In order to protect manpower, workers' hazard exposure must be taken care of. The safety regulation was issued by the U.S. Occupational Safety and Health Administration (OSHA). OSHA was created by the Congress of the United States under the Occupational Safety and Health Act since in 1970. Their mission is to prevent work-related injuries, illnesses, and occupational fatality. They issue and enforce standards for workplace safety and health. OSHA federal regulations covers most private sector workplaces. According to the safety regulations, daily hazard exposure of workers must not exceed the permissible limit which depends on the type of hazards – single limit hazards and variable limit hazards. Hierarchical approaches are suggested, namely, engineering approach, administrative approach, and the use of personal protection equipment. Unfortunately, most strategies are not cost effective and many times seems to be limited in practice. As a good compromised strategy between cost and effectiveness, job rotation is practically implemented.

Job rotation is one a well know tool for workforce management which can lead to contributions for employees and companies. Workers are rotated among the tasks periodically within each day. The total hazard exposure can be alleviated among a group of workers, thus none of them are exposed to hazards over a permissible limit. Job rotation can prevent injuries, reduce employee boredom, balance workload, and improve work skill. Moreover, it's affects employee morale and productivity. However, the periods of rotation should not be too short (i.e., less than 2 hours) because of the effects to learning ability of workers. Job rotation is found to be most suitable to cover construction work schedules. Including job rotation in workforce scheduling is not new. These are common in general health care systems; however, the schedule is not drawn in detail. Only workday or shift-change horizons are usually of consideration in early research studies. Bartholdi et al. (1979) considered cyclic staffing problems. The aim was to schedule a minimum cost workforce so that sufficient workers are on duty during each time period. The problem was transformed to the integer linear program to a bounded series of network flow problems. They presented a round-off algorithm allowing the problem to be solved as a continuous linear program. The solution techniques are shown to extend to more general cyclic staffing problems such as cyclic staffing with overtime, days-off scheduling, cyclic staffing with part-time workers, and cyclic staffing with linear penalties for understaffing and overstaffing. Alfares (1998) developed an efficient two-phase algorithm for cyclic (5, 7) days-off scheduling. Over a given workweek, each worker is provided 5 successive workdays and 2 consecutive days-off. Briefly, a simple expression is used in computing the minimum workforce size to be included as a constraint in a linear programming (LP) model. The results shown to be more efficient than the integer linear programming and the continuous LP procedure (Bartholdi et al., 1979). Alfares (2002) presented an efficient optimum solution is for a real-life employee (14, 21) days-off scheduling problem with a three-week cycle. The solution technique utilizes the dual LP solution to determine the minimum number of workers and feasible days-off assignments, without using linear or integer programming. Later, he developed a new integer programming model and a two-stage solution method was for the flexible 4-day workweek scheduling problem with weekend work frequency constraints (Alfares, 2003). Musliu et al. (2002) constructed a new framework that includes four main steps with backtracking algorithm to rotate workforce schedules. They indicated that rotating workforce schedules have a profound impact on the health and satisfaction of employees as well as on their performance. For large-sized problems, Musliu (2003) appiled tabu search based algorithm, heuristic method based on min-conflicts heuristic, and their combinatorial and variations. Later, Morz and Musliu (2004) presented a genetic algorithm to solve the cyclic rotating workforce scheduling problem.

Job rotation in workforce scheduling problem or job rotation scheduling is known to be difficult in implementation. It is complex due to the numbers of constraints needed to be satisfied. Moreover, at most realistic constraints need to be included. The simplified models of workforce scheduling problem might be even useless in practices. Job rotation involves two main factors, namely, workers and tasks. These two factors are required to be considered as close to the real situations as possible. Seçkiner and Kurt (2007) used job rotation scheduling to balance workload cost by reducing exposure to strenuous jobs. The objective tries to minimize the workload cost among workers in which each worker must receive constant number of day-off each week. The job rotation for workload balancing in human based assembly systems was proposed by Michalos et al. (2010) and job rotation considered employee boredom and skill variation was studied by Azizi et al. (2010). Raina and Dickerson (2009) investigated two tasks that involved the deltoid muscle and found that the effectiveness of rotating between different tasks can reduce muscular fatigue or exposure.

Those previous researches, mostly did not determined hazard exposure in quantitative amounts. Workers are assumed to be safe when performing tasks according to the number of workdays or shift assignment. Determining off-days in each workweek is not enough to prevent workers from exposure to hazards over permissible limits. Seriously, the total amount of hazard exposure in each task are not equal. Since workers are assigned to do one task all day in a workday, workers who perform high hazardous tasks might get the total hazard exposure much more than others (even they get 2 off-days in the end of workweek). The hazard exposure is accumulated in them resulting in health problems in this group of workers. Cyclic work schedule are required to be determined in more detail i.e., rotating tasks within a workday.

To ensure the protection from hazard exposure of workers are under the permissible limit, a few previous literatures conducted job rotation for periods in a workday. The amounts of hazard exposures were evaluated in quantitative numbers. Nanthavanij and Yenradee (1999) developed a mathematical model for the problem with equal numbers of workers and tasks. Their solution described the rotating work schedules such that the maximum noise hazard exposure is minimized. Nanthavanij and Yenradee (2000a) investigated the effect of work period length on the noise hazard reduction. Later, they developed a mathematical model to determine the minimum number of workers for job rotation when operating noisy machines (Nanthavanij & Yenradee, 2000b). Workers' exposures must not exceed the permissible noise exposure level. For the complex safety-based job rotation problem, the swap heuristic was proposed (Yaoyuenyong & Nanthavanij, 2003). A genetic algorithm (GA) (Nanthavanij & Kullpattaranirun, 2001) and a heuristic GA (Kullpattaranirun & Nanthavanij, 2005) were applied to solve large minimax work assignment problem. A heuristic genetic algorithm for minimax assignment problem was presented considering both the balanced and unbalanced number of worker and workstation. Otto and Scholl (2013) presented the ergonomic job rotation scheduling problem (EJRSP) in the automobile industry, this EJRSP is aimed at smoothing ergonomic risks between workers by minimizing the ergonomic load for the worker most exposed to ergonomic risks. The objective function contributes to balancing the risks of all workers in the schedule. The results show that EJRSP is NP-hard in the strong sense. Wongwien and Nanthavanij (2012) proposed ergonomic workforce scheduling with complex worker limitation and task requirement, the problem considers realistic worker limitation and task requirements that include heterogeneous workforce with limited task flexibility, varying number of workers for each tasks, and pre-defined task operation schedules. The objective is to find the minimum number of workers in a single workday planning period. An occupation noise exposure in a sawmill operation was proposed by Tharmmaphornphilas et al. (2003). The mathematical model was developed and intended to minimize the maximum daily noise exposure encountered among the workers. The results suggest that a mathematical modeling approach can reduce worker exposure to occupational noise. Carnahan et al. (2000) introduced job rotation scheduling that reduces the potential for back injury. The objective aims at balancing a Job Severity Index (JSI) that was used to assess the potential for back injury, between workers by minimizing the JSI of most exposed worker. Employees are classified by gender and lifting capacity of employees that effect to exposure of JSI. Aryanezhad et al. (2009) proposed a safe skill-based job rotation scheduling (SSJRS) for multi-working day schedule duration in the manufacturing system that noise exposure and low back injury are simultaneously considered. The first objective function aims to minimize maximum occupational noise exposure, and the second one is designed to minimize the potential of worker’s low back injuries. Noise exposure and low back injuries are assessed by JSI and daily noise dosage (DND), respectively. LP-metric method is used to trade-off solution between DND and JSI, and solving by LINGO.

When the minimum number of workers for job rotation is to be determined, the WSP is proved to be a variant of the classic bin packing problem which is a well-known NP-hard problem (Yaoyuenyong, 2006). Thus, the optimal rotating work schedule solution is obtainable only when the problem size is relatively small. For large problems, a heuristic approach is usually suggested. Yaoyuenyong and Nanthavanij (2006) developed four solution algorithms and a hybrid procedure to determine an optimal workforce without being exposed to excessive noise hazard in the manufacturing environment. Additionally, they developed heuristic job rotation procedures for workers who are exposed to single-limit and multiple-limit occupational hazards (Yaoyuenyong & Nanthavanij, 2008).

2.3.2 Productivity

System productivity is an important factors when construct effective workforce schedule. Good resource management are needed especially when the resources (i.e., manpower or machine hours) are limited. It helps to eliminate losses; as a result, leading to higher profits without any investment. Achieving high total system productivity can be done by either increasing production rate or decreasing various losses. Since a few extra investments are always required to improve productivity rate, many organizations choose to reduce many types of loss instead. Utilizing manpower in ineffective ways can be classified as a type of loss. Productivity, it is regular for management to seek a workforce scheduling solution with high productivity. When assigning a worker to a job that he/she can perform the most effectively, it is reasonable to expect high performance from such worker-job assignment especially in the workforce scheduling problem.

High productivity aspect often included in various machine scheduling. Arroyo and Armentano, (2005) and Chang et al., (2008) used a genetic algorithm to investigate multiobjective flowshop scheduling problem. Makespan and maximum tardiness are considered to be minimized. Details of algorithms in each part are clarified in the literatures. Yagmahan and Yenisey, (2010) treated the problem by using multi-objective ant colony system algorithm, which combines the ant colony optimization approach and a local search strategy. The objective is formulated as minimizing the weighted combination of makespan and total flowtime. For other related literatures, see the research by Sha and Lin, (2010), Chang et al. (2007) and Ip et al. (2000).

In the area of workforce scheduling, there are only small numbers of research focusing on the high total productivity. Chu and Sydney, (2007) studied real applications in the Hong Kong International Airport. Goal programming models were utilized for an integrated problem of crew duties assignment which were decomposed into its duties generating, scheduling, and rostering phases. They proposed both GP based model and extended version in minimizing idle shifts. Dohn et al. (2009) focused on maximizing the total number of assigned tasks by presenting an integer programming model using Dantzig–Wolfe decomposition. The problem was divided into a generalized set-covering the master problem and an elementary shortest path pricing problem. Then, the models were solved by column generation in a branch-and-price framework.

As an effect of job rotation, total system productivity might be reduced. A few workers who are proficient in different tasks might be rotated to other tasks due to safety constraints. Thus, instead of reaching in one objective as previous research, hybrid consideration between the total system productivity and workers' safety should be determined. Nanthavanij et al. (2010) included the productivity issue in their rotating workforce study. A safety-productivity workforce scheduling model and a heuristic approach were presented to find appropriate work schedules such that workers are assigned to the tasks that they can perform competently and workers' hazard exposure are of consideration at the same time. This research provided broader view to combination of ergonomics and workforce scheduling. Indeed, the number of work-task changeover also affect to the total system productivity. It is obvious that workers need at least a short period of time to travel to another workplace or setting the new workstation before starting up a new assigned task. This consuming time practically can lead to a major loss. Thus, the number of work-task changeovers should be kept at minimum when implementing job rotation.

2.3.3 Others (satisfaction, worker and task factors)

It is a fact that workers who perform their preferable tasks and/or with preferred partners usually tend to conduct spotless work. Happiness in the workplace environment helps to reduce turnover rate, resulting in a lower human resourcing management cost. Currently, employee's preferences have become an important issue when constructing a work schedule. Stolletz, (2010) studied hierarchical workforce staffing for check-in systems at airports. Individual employee preferences were included in their extended model. The preferences were provided in terms of preferred days-off, period of earliest shift-start, and period latest shift-end. A few additional constraints were added to avoid such large differences in starting periods of consecutive shifts as well. A binary linear programming with a reduced set-covering formulation was developed for the underlying problem. The model was tested with real-world demand data. Maenhout and Vanhoucke (2010) presented a hybrid scatter search algorithm for the airline crew rostering problem. The objective was to assign a personalized roster to each crew member minimizing the overall operational costs, ensuring impartiality and fairness of crew members, and satisfying crews' preferences for certain roster attributes. Crew members consisted of 3 types (e.g., regular, extra, and freelance) depending on their work skills. The problem was broke up into a master rostering problem and a subproblem based on the Dantzig–Wolfe decomposition. The master problem was modeled as a generalized set partitioning problem while the subproblem was modeled as a network problem. Jaturanonda and Nanthavanij (2005) considered the employee's preferences, but unlike the other researches, the point of competency was also taken into account. In the same fashion, see Peters and Zelewski (2007). Akbari et al. (2013) considered part-time and mixed-skilled workers scheduling problem. Unlike any other research, variable workers' productivity during a day is of consideration. Workers' fatigue is stated to influence worker performance and, consequently, rate of production. Thus, ratio of output decreased along consecutive work shifts. The objective was set to maximize workers' satisfaction while regarding workers' availability, productivity, priority preference, seniority level, and number of workers required. Simulated annealing (SA) and variable neighborhood search (VNS) were introduced to the problem. The results indicated that performance of VNS was better than that of SA in terms of both solution quality and computation time. Although, modern research trends to cover more worker preference aspects, workers' preferred partners cannot be found in any of them.

As one can see from the literature reviews, differences in work skills of employees are obvious and nowadays has become one of the most important factors which needs to be covered. It is the fact that workers are heterogeneous. Even when performing the same tasks, they provide different work skills. Sometimes workers are assigned to tasks that they are not competent in which leads to the total system productivity decreasing. Hence, it is essential to “put the right man in the right job”. Many literatures from the past have considered heterogeneous workers. Previously, workers were considered to be heterogeneous in terms of different work skills, for example, reseach of Narasimhan (1997). Billionnet (1999) determined hierarchical workforce scheduling problem. Workers are classified into categories arranging their capabilities hierarchically. Workers who have a higher qualification could substitute for a lower qualification one, but not vice versa. The labor requirements might vary from one category to the others, however, the numbers of workers in each category have to satisfy the labor and off-days requirements. Thompson and Goodale (2006) considered the problem of developing workforce schedules using groups of employees having different productivity. They divided workers into two main groups – higher and lower than mean productivity.

Later, multiskill workers and limited ability were included. A few workers might be cross-trained, so they can perform more than only one type of tasks. Cai and Li (2000) presented a genetic algorithm to schedule staff of mixed skills under multi-criteria. Workers’ limited ability was taken into account. There are three types of workers: type-1 worker can do only type-1 task; type-2 worker can do only type-2 task; and type-3 worker can do both type-1 and type-2 task. However, type-3 workers consume more staff cost. Researchers extended to cover more realistic case that a few workers might have no skill level due to new employed or unqualified certificate. Fowler et al. (2008) presented two linear programming (LP) based to heuristics, a solution space partition approach, and GA to consider the optimal number of workers in each skill level in each period so as to achieve the minimum total cost. Skill of workers refers to machine groups that they can operate. New hired workers are included by representing as an empty skill. Hojati and Patil (2011) applied integer programming (IP) in conjunction with the heuristic approach to schedule heterogeneous, part-time service employees with limited availability. Employees have different availability and skills, and work different total work hours in a workweek. The objectives are to minimize over staffing and to meet the target total work hours for each employee during the planning period. The problem is decomposed into two sub problems and solved by integer linear programs. Other examples of work skill consideration are in terms of: different work skill workers

(Billionnet, 1999; Ho & Leung, 2010; Remde et al., 2007), mixed skill workers (Rong, 2010), and mutiskill workers (Avramidis et al., 2010; Gomar et al., 2002; Heimerl & Kolisch, 2010; Kuo et al., 2014; Yan et al., 2004).

For the task constraints, many types of tasks require more than one worker to operate at a time. It is called a worker team. Ho and Leung (2010) studied a manpower scheduling problem with job time windows and job-skills compatibility constraints. In this research, each driver/loader had skills to service a few, but not all, of the airline/aircraft/configuration of the jobs – multiskill. Worker had to be formed as a worker team with the appropriate skills in order to service a certain flight. Other research claimed the worker team as assigning a set of workers to a set of tasks (Dohn et al., 2009), not scheduling workers to become a worker team. Apart from single or multiple worker operation, task operation schedule should be considered. It is the fact that each task has its operation schedule indicating when the machines or operation should be off, for example, shutting down in order to do daily corrective maintenance. Assigning workers to perform a set of tasks must be depending upon these task factors. From previous literatures, there has been no research which combined worker and task constraints simultaneously.

Chapter 3
Multi-workday Ergonomic Workforce Scheduling (MW-EWSP)

Based on the optimization approach, a mathematical model is developed to optimize three-conflict objectives simultaneously under the worker and task constraints. The multi-objectives solved as LP-metric method addressed here are: (1) minimum fluctuate hazard exposure of workers' group (Objective 1:OB1), (2) maximum total productivity scores (Objective 2:OB2), and (3) minimum number of dissatisfies pair both task and partner (Objective 3:OB3). A heterogeneous workforce is considered. They are different in their ability to perform a tasks. However, hazard exposure of every worker is limited under the permissible limit. Each task or workstation is varied in number of required worker to perform together and its operation schedule on multi-workday planning period.

3.1 Problem Description

The problem emphasis on construct schedules for multi-workday in the workplace environment when workers or employees are exposed to ergonomic hazards. According to the safety laws, workers must not be exposed to a given occupational hazard beyond permissible daily limits. A worker limitation and workstation operation schedule are considered, the workers are heterogeneous that each worker can do a specific job or task upon his/her qualification. The operation schedule of workstation is predetermined for all days in the planning period. If the workstation off schedule, all tasks in this station must off operation. The workday can be divided into multiple work periods, workers are rotated to perform several tasks or workstation during the workday to reduce their hazard exposures. The objective of this problem is to determine three inconsistent objectives solution for multi-workday scheduling by considering a single-limit hazard at the workstation.

A single-limit ergonomic hazard exposure at the workstation is studied with permissible exposure limits which are the same for every person. This single hazard exposure can be classified into 2 types, a uniform hazard exposure and a non-uniform hazard exposure. Firstly, a uniform hazard exposure at the workstation. For this hazard type, a worker performing each task at workstation is exposed to the same hazard level if the workstation has more than one task to perform. Based on each task has a short distance among tasks in the workstation. The examples of this hazard type are noise, heart, cold, radiation, and toxic chemicals. Secondly, a non-uniform hazard exposure at the workstation. Unlike its previous hazard type, each task in the workstation has a different hazard exposure level. The hazard exposure level at each task in workstation is up to physical qualification of workers, a worker who is stronger than other workers is exposed to less hazard level at the same task. The examples of this hazard type are lifting injuries access by JSI, mental stress, etc.

In this research, three criteria are considered when generating safe multi-workday rotation work schedules for industrial workers.

1) Hazard exposure balancing, past research studies were only concerned with finding either optimal or near-optimal solutions for one day. This is perhaps based on an assumption that the workers' work schedules will be the same as long as job requirement do not change. These fixed work schedules can lead to unfair worker-task assignments for a few workers since they could be assigned to more hazardous tasks than other workers. A multi-workday planning period could be used to avoid uneven hazard exposure among worker on multi-workday operation. Moreover, even hazard exposure can reduce dangerous and indirectly boost employee safety and satisfaction.

2) Productivity, it is regular for management to seek a workforce scheduling solution with high productivity. When assigning a worker to job that he/she can perform effectively, it is reasonable to expect high performance from such worker-job assignment. In other words, the productivity directly relates to the person-job fit score. When solving EWSP based on this aspect, workers are likely to be assigned to jobs that match the high person-job fit score.

3) Satisfaction, it has been known that satisfied workers are efficient workers. As far as the worker-job assignment is concerned, each worker has his/her own preferred job(s) and/or work partner(s) (when being assigned to a team). It is clear that when the worker is assigned to the preferred job or paired with preferred partner(s), he/she is well satisfied with such assignment. Job satisfaction is normally associated with high productivity and low turnover rate. When generating safe multi-

workday rotating work schedules, it is advisable to consider the preference lists of involved workers regarding their preferred jobs and partners.

When the MW-EWSP is independently solved according to one of the above three criteria at a time, it is expected that the results (i.e., safe daily rotating work schedule) are different in terms of the hazard exposure balancing, productivity, and satisfaction. Thus, when the MW-EWSP is considered as a single objective optimization problem, its solution depends on the criterion that a decision maker chooses as the problem goal. Certainly, when considered each objective as a single objective optimization problem, the results might be sacrificed with other objectives. The MW-EWSP becomes more complex when two or more criteria are considered. The problem can be solved by considering the concerned criteria sequentially or all at once simultaneously.

3.2 Assumptions and Conditions

The formulation of MW-EWSP mathematical model requires the following assumptions and conditions.

3.2.1 Assumptions

1. A workday is divided into equal work periods. Job rotation occurs only at the end of the work period. There are a group of workers which are sufficient for the schedules and do not violated permissible limit within each workday.

2. In any given work period in each day, a workstation may or may not to be performed depending on its operation schedule.

3. The number of workers required to perform at a different workstation do not have to be equal up to the number of task at workstation.

4. The numbers of tasks that the workers can perform are known and do not have to be equal.

5. The hazard exposures per period at each task or workstation and the permissible daily limit of hazard exposure are known and constant.

6. The person-job fit score and preferred tasks/partner(s) are known.

3.2.2 Conditions

1. Each worker must not be exposed to a given hazard exposure beyond a permissible limit within each workday.

2. Predetermined suitable of the number of workers for job rotation. All workers must be utilized on each workday.

3. In each work period, each worker can be assigned to only one task.

4. If a workstation is in operation, all tasks at the workstation must be operated and it must be satisfied by assigning a worker to each task. If a workstation is in the off operation (shutdown), all tasks at the workstation must not be operated and none assigned to the worker.

5. Constraints on the work station operation schedule, worker limitation, must not be violated.

3.3 Mathematical Model

Before solving the multi-objective consideration, the desired goal value for each objective of MW-EWSP model must be obtained. The single-objective MW-EWSP model for hazard exposure balancing, productivity and satisfaction are formulated as Mixed Integer Linear Programming (MILP). Then, solving each objective and set as the desired goal value in multi-objective model is conducted. The multi-objective MW-EWSP model are also formulated as MILP, the problem is considered as multi-objective MW-EWSP with LP-metric method that solves multi-objective solution simultaneously which are the important weights defined for each considered aspect.

3.3.1 Single-objective MW-EWSP model

The notations are shown as follows:

<u>*Parameters*</u>*:*

a_{ijl} 1 if worker i can perform task l in work station j; 0 otherwise

h_{jl} hazard exposure per work period of task l in work station j

I number of utilized workers; $i \in \{1,\ldots,I\}$

J number of work station; $j \in \{1,\ldots,J\}$

K number of work period per workday; $k \in \{1,\ldots,K\}$

L daily permissible limit of hazard exposure

N_j number of task in work station j; $l \in \{1,\ldots,N_j\}$

p^t_{jk} 1 if work station j has to perform in work period k on day t; 0 otherwise

pp_{in} 1 if worker i chooses worker n as his/her preferred team to perform a work station ; 0 otherwise

pt_{ijl} 1 if worker i chooses task l of work station j as his/her preferred task; 0 otherwise

s_{ijl} person-job fit score of worker i perform task l of work station j

T number of workday in planning period; $t \in \{1,\ldots,T\}$

Decision variables:

TD total number of dissatisfied worker– task and worker-team assignment

TSC total person-job fit score

USP^t_{injk} 1 if worker i is teamed up with non-preferred worker n to perform workstation j in work period k of day t

0 otherwise

UST^t_k total number of dissatisfied worker – task paring in work period k of day t

X^t_{ijlk} 1 if worker i is assigned to preform task l of workstation j in work period k on workday t

0 otherwise

Z maximum average hazard exposure among workers

1. Sub-model Z (OB1)

The single-objective MW-EWSP model for hazard exposure balancing can be described as follows.

$$\text{Minimize } Z \tag{3.1}$$

Subject to

$$\sum_{j=1}^{J}\sum_{l=1}^{N_j}\sum_{k=1}^{K} h_{ijl} X^t_{ijlk} \le L \qquad i \in I,\, t \in T \tag{3.2}$$

$$\frac{\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{l=1}^{N_j}\sum_{k=1}^{K} h_{ijl} X^t_{ijlk}}{T} \le Z \qquad i \in I \tag{3.3}$$

$$\sum_{j=1}^{J}\sum_{l=1}^{N_j} X^t_{ijlk} \le 1 \qquad i \in I,\, k \in K,\, t \in T \tag{3.4}$$

$$\sum_{i=1}^{I} X_{ijlk}^{t} = p_{jk}^{t} \qquad j \in J, l \in N_j, k \in K, t \in T \qquad (3.5)$$

$$\sum_{j=1}^{J}\sum_{l=1}^{N_j}\sum_{k=1}^{K} X_{ijlk}^{t} \geq 1 \qquad i \in I, t \in T \qquad (3.6)$$

$$X_{ijlk}^{t} \leq p_{jk}^{t} \qquad i \in I, l \in N_j, j \in J, k \in K, t \in T \qquad (3.7)$$

$$X_{ijlk}^{t} \leq a_{ijl} \qquad i \in I, l \in N_j, j \in J, k \in K, t \in T \qquad (3.8)$$

$$X_{ijlk}^{t} \in \{0,1\} \qquad i \in I, l \in N_j, j \in J, k \in K, t \in T \qquad (3.9)$$

Objective (3.1) tries to balance hazard exposure by minimizing maximum average of hazard exposure among workers of planning period. Constraint (3.2) states that for any worker, the sum of hazard exposure amounts that a worker receives during the workday does not exceed the daily permissible limit *L*. Constraint (3.3) ensures that average hazard exposure of a worker must not excessive maximum average hazard exposure. Constraint (3.4) specifies that a worker can be assigned to perform at most one task per period. Constraint (3.5) states all workstation operations in each period must have the required worker to perform all tasks in that workstation. Constraint (3.6) states that all workers must be utilized in each workday. Constraint (3.7) specifies that workers can only be assigned to workstations that operate in that period. Constraint (3.8) prevents workers performing tasks that he/she has no skill to perform. Constraint (3.9) defines binary decision variables.

2. Sub-model TSC (OB2)

The single-objective MW-EWSP model for productivity can be described as follows.

Maximize *TSC* (3.10)

Subject to

$$\sum_{j=1}^{J}\sum_{l=1}^{N_j}\sum_{k=1}^{K} h_{ijl} X_{ijlk}^{t} \leq L \qquad i \in I, t \in T \qquad (3.11)$$

$$\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{l=1}^{N_j}\sum_{k=1}^{K} s_{ijl} X_{ijlk}^{t} = TSC \qquad (3.12)$$

$$\sum_{j=1}^{J}\sum_{l=1}^{N_j} X_{ijlk}^{t} \le 1 \qquad i \in I, k \in K, t \in T \qquad (3.13)$$

$$\sum_{i=1}^{I} X_{ijlk}^{t} = p_{jk}^{t} \qquad j \in J, l \in N_j, k \in K, t \in T \qquad (3.14)$$

$$\sum_{j=1}^{J}\sum_{l=1}^{N_j}\sum_{k=1}^{K} X_{ijlk}^{t} \ge 1 \qquad i \in I, t \in T \qquad (3.15)$$

$$X_{ijlk}^{t} \le p_{jk}^{t} \qquad i \in I, l \in N_j, j \in J, k \in K, t \in T \qquad (3.16)$$

$$X_{ijlk}^{t} \le a_{ijl} \qquad i \in I, l \in N_j, j \in J, k \in K, t \in T \qquad (3.17)$$

$$X_{ijlk}^{t} \in \{0,1\} \qquad i \in I, l \in N_j, j \in J, k \in K, t \in T \qquad (3.18)$$

Objective (3.10) is to maximize the total person-job fit score. Constraint (3.12) sums up the total person-job fit score.

3. Sub-model TD (OB3)

The single-objective MW-EWSP model for satisfaction can be described as follows.

Minimize TD (3.19)

Subject to

$$\sum_{j=1}^{J}\sum_{l=1}^{N_j}\sum_{k=1}^{K} h_{ijl} X_{ijlk}^{t} \le L \qquad i \in I, t \in T \qquad (3.20)$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{l=1}^{N_j} X_{ijlk}^{t} - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{l=1}^{N_j} pt_{ijl} X_{ijlk}^{t} = UST_k^{t} \qquad k \in K, t \in T \qquad (3.21)$$

$$\left[\left(\sum_{l=1}^{N_j} X_{ijlk}^{t} + \sum_{l=1}^{N_j} X_{njlk}^{t}\right) - 1\right] - pp_{in} \le USP_{injk}^{t} \qquad i \in I, n \in I, i \ne n; j \in J \; k \in K, t \in T \qquad (3.22)$$

$$\sum_{t=1}^{T}\sum_{k=1}^{K} UST_k^{t} + \sum_{i=1}^{I}\sum_{n=1}^{I}\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{k=1}^{K} USP_{injk}^{t} = TD \qquad (3.23)$$

$$\sum_{j=1}^{J}\sum_{l=1}^{N_j} X_{ijlk}^{t} \le 1 \qquad i \in I, k \in K, t \in T \qquad (3.24)$$

$$\sum_{i=1}^{I} X_{ijlk}^{t} = p_{jk}^{t} \qquad j \in J, l \in N_j, k \in K, t \in T \qquad (3.25)$$

$$\sum_{j=1}^{J}\sum_{l=1}^{N_j}\sum_{k=1}^{K} X_{ijlk}^{t} \geq 1 \qquad i \in I, t \in T \qquad (3.26)$$

$$X_{ijlk}^{t} \leq p_{jk}^{t} \qquad i \in I, l \in N_j, j \in J, k \in K, t \in T \qquad (3.27)$$

$$X_{ijlk}^{t} \leq a_{ijl} \qquad i \in I, l \in N_j, j \in J, k \in K, t \in T \qquad (3.28)$$

$$X_{ijlk}^{t} \in \{0,1\} \qquad i \in I, l \in N_j, j \in J, k \in K, t \in T \qquad (3.29)$$

Objective (3.19) is to minimize sum up the total dissatisfied worker-task and worker-partner assignment from all utilized workers. Constraint (3.21) counts the number of dissatisfied worker-task. Constraint (3.22) counts the number of dissatisfied worker-partner assignments. For the job with two workers (say, worker *a* and *b*), the satisfied worker-partner assignment is counted when worker *a* is satisfied with begin paired with worker *b*, or when worker *b* is satisfied with paired with worker *a*. If both workers are satisfied, then there are 2 satisfied worker-partner assignments. Constraint (3.23) sums up the total number of dissatisfied from total number of dissatisfied worker-task assignment plus total number of dissatisfied worker-partner assignment.

3.3.2 Multi-objective MW-EWSP model

For multi-objective MW-EWSP model, the solution from sub-model Z, TSC and TD in section 3.3.1 are defined as Z^*, TSC^* and TD^* respectively. The addition notations are shown as follows:

<u>*Parameters*</u>*:*

- MS total number of all possible satisfaction (both task and team assignment)
- TD^* desired goal value of total number of dissatisfied worker– task and worker-team assignment
- TSC^* desired goal value of total person-job fit score
- TSF^* desired goal value of total number of satisfaction equal MS minus TD^*
- w_1 important weights of LP-metric objective function for objective 1 (OB1)
- w_2 important weights of LP-metric objective function for objective 2 (OB2)
- w_3 important weights of LP-metric objective function for objective 3 (OB3)
- Z^* desired goal value of maximum average hazard exposure among worker

Decision variables:

TD total number of dissatisfied worker– task and worker-team assignment

TSC total person-job fit score

TSF total number of satisfaction

USP_{injk}^{t} 1 if worker i is teamed up with non-preferred worker n to perform workstation j in work period k of day t

0 otherwise

UST_{k}^{t} total number of dissatisfied worker – task paring in work period k of day t

X_{ijlk}^{t} 1 if worker i is assigned to preform task l of workstation j in work period k on workday t

0 otherwise

Z maximum average hazard exposure among workers

Objective function:

$$\text{Minimize}\left[w_1\frac{Z-Z^*}{Z^*}+w_2\frac{TSC^*-TSC}{TSC^*}+w_3\frac{TSF^*-TSF}{TSF^*}\right] \tag{3.30}$$

Model constraints:

$$\sum_{j=1}^{J}\sum_{l=1}^{N_j}\sum_{k=1}^{K}h_{ijl}X_{ijlk}^{t}\le L \qquad i\in I,\ t\in T \tag{3.31}$$

$$\frac{\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{l=1}^{N_j}\sum_{k=1}^{K}h_{ijl}X_{ijlk}^{t}}{T}\le Z \qquad i\in I \tag{3.32}$$

$$\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{l=1}^{N_j}\sum_{k=1}^{K}s_{ijl}X_{ijlk}^{t}=TSC \tag{3.33}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{l=1}^{N_j}X_{ijlk}^{t}-\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{l=1}^{N_j}pt_{ijl}X_{ijlk}^{t}=UST_{k}^{t} \qquad k\in K,\ t\in T \tag{3.34}$$

$$\left[\left(\sum_{l=1}^{N_j}X_{ijlk}^{t}+\sum_{l=1}^{N_j}X_{njlk}^{t}\right)-1\right]-pp_{in}\le USP_{injk}^{t} \qquad i\in I,\ n\in I, i\neq n;\ j\in J\ \ k\in K,\ t\in T \tag{3.35}$$

$$\sum_{t=1}^{T}\sum_{k=1}^{K}UST_{k}^{t}+\sum_{i=1}^{I}\sum_{n=1}^{I}\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{k=1}^{K}USP_{injk}^{t}=TD \tag{3.36}$$

$$TSF = MS - TD \tag{3.37}$$

$$\sum_{j=1}^{J}\sum_{l=1}^{N_j} X_{ijlk}^{t} \le 1 \qquad i \in I,\ k \in K,\ t \in T \tag{3.38}$$

$$\sum_{i=1}^{I} X_{ijlk}^{t} = p_{jk}^{t} \qquad j \in J,\ l \in N_j,\ k \in K,\ t \in T \tag{3.39}$$

$$\sum_{j=1}^{J}\sum_{l=1}^{N_j}\sum_{k=1}^{K} X_{ijlk}^{t} \ge 1 \qquad i \in I,\ t \in T \tag{3.40}$$

$$X_{ijlk}^{t} \le p_{jk}^{t} \qquad i \in I,\ l \in N_j,\ j \in J,\ k \in K,\ t \in T \tag{3.41}$$

$$X_{ijlk}^{t} \le a_{ijl} \qquad i \in I,\ l \in N_j,\ j \in J,\ k \in K,\ t \in T \tag{3.42}$$

$$X_{ijlk}^{t} \in \{0,1\} \qquad i \in I,\ l \in N_j,\ j \in J,\ k \in K,\ t \in T \tag{3.43}$$

Objective (3.30) tries to minimize deviation of the LP-metric objective function. Constraint (3.37) computes total number of satisfied.

Chapter 4
Genetic Algorithm Approach for MW-EWSP

This chapter explains the genetic algorithm (GA) in detail. Mainly, this chapter is divided into 3 sections. Section 4.1 presents the concept of the GA procedure. The GA operation is clarified in section 4.2. Chromosome representation, creation of the initial population, fitness scaling, penalty value and fitness function, selection and reproduction, GA parameters, and termination condition are discussed.

4.1 GA Procedure

The genetic algorithm is one of the most popular metaheuristic for combinatorial optimization. Firstly introduce by Holland (1992), the algorithm tries to emulate the process of natural selection of evolutionary in search procedure. The GA procedure based on MATLAB genetic algorithm tool is presented in figure 4.1.

Input : Problem data, GA parameters
Output : Best solution
Begin
    $t \leftarrow 0$;
    Generate initial population $P(t)$ by encoding routine;
While (not terminating condition**) do**
    evaluate $P(t)$ by decoding routine;
    select $R(t)$ from $P(t)$ by selection routine;
    create $C(t)$ from $R(t)$ by crossover routine;
    create $C(t)$ from $R(t)$ by mutation routine;
    elitism best solution to $P(t + 1)$
    add remain $P(t + 1)$ from entire $C(t)$;
    $t \leftarrow t + 1$;
End
Output the best solution
End

Figure 4.1 The GA procedure

The procedure in figure 4.1, $P(t)$ represents the population in generation t , $R(t)$ represents the parent chromosome in generation t , and $C(t)$ represents the offspring chromosome in generation t , beginning with the encoding part, a set of initial population is created. Then, it is sent to the evaluation part to decode chromosomes and compute their fitness values by decoding routine. The step of selection is used to select parents chromosome and reproduction as offspring by crossover and mutation routine. For the reproduction, order crossover, swap mutation, and elitism are employed to produce the next generation population. After that, a new generation of population will be sent to the evaluation step. The loop will be continued until GA reaches the termination condition and return best solution.

4.2 GA Operations

4.2.1 Chromosome representation

Asawarungsaengkul and Nanthavanij (2008) proposed permutation encoding for multi-period of single workday job rotation. From their encoding, the adaption extends to encode multi-workday assignment solution as single chromosome by adding the next workday chromosome to right hand side of previous workday chromosome until end of planning period. Figure 4.2 shows a chromosome representation of the work assignment problem in one workday and four work period as a string. The chromosome string is divided into k segments, where each segment represents a work period. In each segment, there are i genes, where each gene represents a task. This chromosome representation each worker to attend only one task in one work period vice versa each task has only one worker to attend in one work period.

Example of chromosome encoding from Figure 4.2, the chromosome of one workday consists of four segments, with seven genes in each segment. There are three workstations, five tasks, and seven workers. The first seven genes show the work assignments for the seven workers (W1 to W7) in work period1, the next four genes for the assignment in work period2, and so on. It should be noted that in each period, the order of assignment is T1 – T5. If the number of task less than the number of workers, the assignment in gene that beyond to the number of task (T6, T7) will be represented an idle work period for this assigned worker. For workstation off schedule, the task assignment in gene represents an idle work period too. The other workday chromosome segments are used in the same scheme as presented.

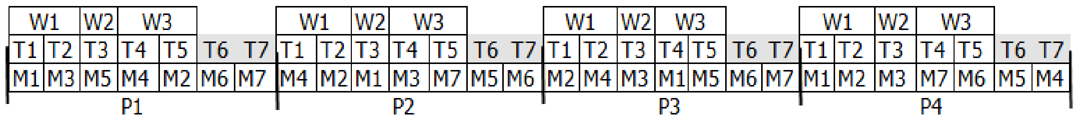


Figure 4.2 Chromosome representation

It is also observed that the length of chromosome string is equal $K\times I\times T$. There are a constant number of chromosomes in the population as denoted by population size.

4.2.2 Initial population

Random permutation is applied for the initial population for each single objective problem (sub-model Z, TSC, TD). Exclusively, for the main-model LP metric, initial population combine of the best solution from sub-model Z (OB1) 34%, sub-model TSC (OB2) 33%, and sub-model TD (OB3) 33% respectively.

4.2.3 Fitness scaling, fitness function, and penalty function

4.2.3.1 Fitness scaling

A fitness scaled value is used to evaluate the quality of chromosomes in each generation. The chromosome receiving a high scaled value will potentially be selected as parents to produce offspring which are included in next generation population. A selection routine is used to select chromosomes to produce offspring. A large scaled value chromosome has a high change to be selected for selection routines. In this procedure, the chromosome with lower fitness evaluation value with more fitness scaled value.

4.2.3.2 Fitness evaluation function

For the sub-model 1 hazard exposure balancing objective (OB1), a fitness value of model with hazard exposure balancing (described by sub-model Z) is defined as the maximum average hazard exposure among workers. A fitness evaluation function of chromosome k can be written as

$$F_1(k) = Z \tag{4.1}$$

For the sub-model 2 productivity objective (OB2), a fitness value of model of productivity (described by sub-model TCS) is defined as the total person-job fit score. This GA procedure tries to minimize fitness value. Thus, strong chromosomes are those chromosomes with low fitness values. A fitness function of chromosome *k* can be written as

$$F_2(k) = \frac{1}{TSC} \tag{4.2}$$

For the sub-model 3 satisfaction objective (OB3), a fitness value of model of satisfaction (described by sub-model TD) is defined as the total number of dissatisfied. A fitness function of chromosome *k* can be written as

$$F_3(k) = TD \tag{4.3}$$

For the multi-objective model, a fitness value of LP-metric method model is defined as the summation of normalized differences between each objective and the optimal values of them.

$$F_4(k) = \left[w_1 \frac{Z - Z^*}{Z^*} + w_2 \frac{TSC^* - TSC}{TSC^*} + w_3 \frac{TSF^* - TSF}{TSF^*} \right] \tag{4.4}$$

4.2.3.3 Penalty function

Since this problem has an upper bound constraint, i.e., each sum of hazard exposure per workday of each worker must not exceed permissible limit, and both conditions constraint i.e., forbid assignment, and utilizing of workers, a penalty term is added to the fitness value so that any chromosome that falls in infeasible solution will have lesser chance to be selected as parent than others. The penalty functions of chromosome *k* using the following function.

1. Excessive hazard exposure beyond permissible *L*

$$\left(\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} X_{ijk}^{t} h_j - L\right) \times \theta = \gamma \text{ for } \sum_{j=1}^{J}\sum_{k=1}^{K} X_{ijk}^{t} h_j - L > 0 \tag{4.5}$$

2. Assignment to the task which cannot operate; Penalty = α (4.6)

3. If not utilizing any worker on each workdays; Penalty = β (4.7)

θ, α, β, = a positive integer value

Penalty value = γ+α+β (4.8)

4.2.4 Selection and reproduction

Selection is the process of choosing two parents from the population for crossing. The purpose of selection is to emphasize better chromosomes in the population with the hope that their offspring have better fitness. In this research, the tournament selection is used to select parents from the population. In tournament selection, T chromosomes are chosen randomly and the chromosome that has the largest scaled value becomes the parent. The next generation population will contain offspring from the crossover, mutation and elitism chromosomes.

4.2.5 Crossover

The main genetic operator is crossover, this stimulates the reproduction between two parents. Crossover is a genetic operation that attempts to create a new chromosome that might be stronger than the old ones. The offspring share a few characteristics of the parents and passed this onto the future generation also. In this operation, order crossover (OX) (see figure 4.3) proposed by Davis (1985) is employed as crossover operator with modified repair forbid assignment. It can be viewed as a kind of variation PMX crossover with a difference repairing procedure. For this problem's chromosome, the OX operates as follows:

Input: two parent chromosomes

Output: one offspring

Step1: select a workday *t* from one parent

Step2: select work period *k* from one parent at random

Step3: select a substring from one parent at random

Step4: produce a proto-child by copying the substring into corresponding positions of selected chromosome.

Step5: swap a miss assignment node (assign worker to his/her incapable task) with a correct node within substring (both exchange must be correct assignment node) do until try to all combinations.

Step6: delete the nodes which already in the substring from second parent.

Step7: Place the nodes into the unfixed positions of the proto-child from left to right according to the order of the sequence to produce an offspring.

Step8: swap a miss assignment node with a correct node outside substring (both exchange must be correct assignment node) do until try to all combinations.

A number of offspring which are produced by crossover is up to the crossover fraction. For example, if the Population size is 20, the elitism is 2, and the crossover fraction is 0.8, the numbers of each type of children in the next generation are as follows: There are two elite children. There are 18 individuals other than elite children, so the algorithm rounds 0.8*18 = 14.4 to 14 to get the number of crossover children. The remaining four individuals are mutation children. For prevent stuck in local optimal and allow GA to through all search space include infeasible space, the repair assignment in step5 and step8 will be applied to only the first 500 generations. This method can help to find feasible results faster than conventional method.

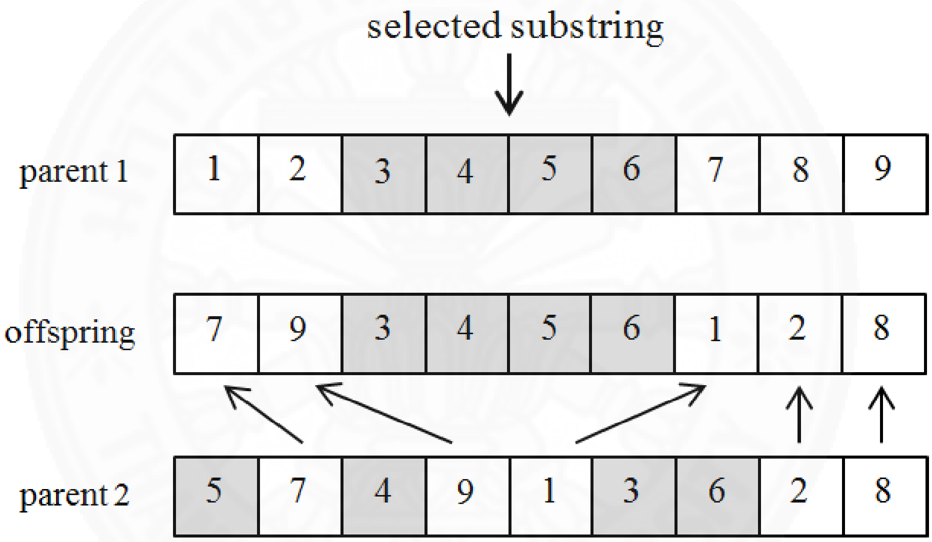


Figure 4.3 Illustration of the OX operator

4.2.6 Mutation

The other genetic operator is mutation which makes random alterations to various chromosomes. The mutation operator makes a small random change in the solution which can prevent to stump in local optimal. In this operation, swap mutation (see figure 4.4) with the additional check limited worker skill is used for the mutation operator. For this problem’s chromosome, the swap mutation works as follows:

Input: one selected parent chromosome

Output: offspring

Step1: select a workday *t* from parent

Step2: select work period *k* from parent at random

Step3: selects two elements at random and checks if swaps these two nodes are not violated limited skill, then swaps the elements on theses position. Otherwise a random new element is generated and repeated. Number of random is set as number of workers in the problem.

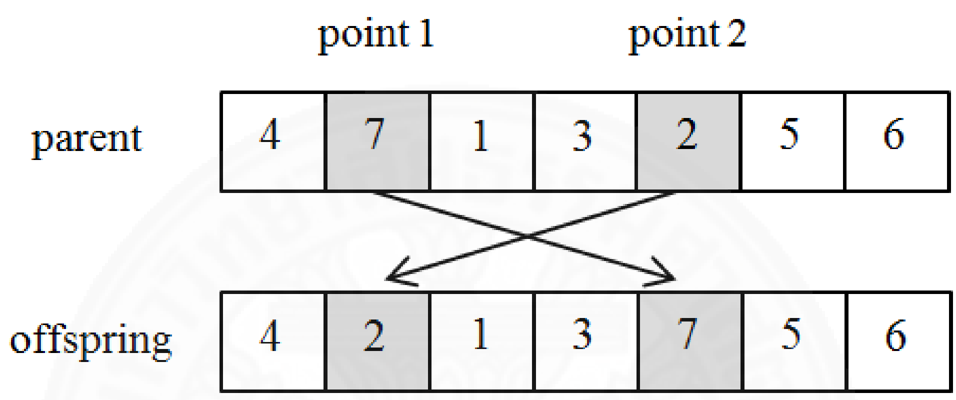


Figure 4.4 Illustration of swap mutation operator

4.2.7 Termination conditions

The GA procedure is terminated when the iteration hits the maximum generation. In addition, the stopping criteria may use both maximum generation and termination time when the problem size is increased.

Chapter 5
Numerical Example

In this chapter, a numerical example is presented in order to determine and compare among the optimization and GA approach. The problem description is descripted and two approaches are implemented for the same numerical example.

5.1 Problem description

Consider hypothetical workplace with a certain ergonomic non-uniform hazard where three workstations (W1 to W3), five tasks (T1 to T5) and six utilized workers (M1 to M6). The planning period was 5 days (D1 to D5). A workday is divided into four equal work periods (P1 to P4). The hazard exposure amount per periods was known and where not time-dependent. For conveniently, it is assumed that permissible daily hazard exposure limit *L* is 1.000. Table 5.1 shows the hazard exposure amounts per work period of task in each workstation. The six utilized workers were flexible and can be assigned to several tasks but with different person-job fit score ranging from 1 (low) to 5 (high). Table 5.2 lists the person-job fit score and preferred task of six workers (The score 0 means that the worker is incapable of performing that task). The preferred partners/teams of all workers are listed in Table 5.3. The operation schedule of workstations is presented in table 5.4.

Table 5.1 Work station and task data

Workstation-task	W1-T1	W2-T2	W2-T3	W3-T4	W3-T5
Hazard amount per work period	0.2607	0.2219	0.1706	0.4423	0.3215

Table 5.2 Person-job fit score matrix/ limit work skill and list of preferred task

(a) person-job fit scores (b) preferred tasks (P=preferred)

Worker	Task					Worker	Task				
	T1	T2	T3	T4	T5		T1	T2	T3	T4	T5
M1	3	0	3	5	2	M1	P	-	-	P	P
M2	0	5	3	0	5	M2	-	P	P	-	-
M3	5	0	4	2	0	M3	P	-	-	P	-
M4	3	5	0	4	2	M4	-	P	-	-	P
M5	5	4	0	2	4	M5	P	-	-	P	-
M6	3	0	4	0	3	M6	-	-	P	-	P

Table 5.3 Preferred partners/teams of the workers

Worker	Partner					
	M1	M2	M3	M4	M5	M6
M1	-	P	P	-	P	P
M2	P	-	-	P	-	-
M3	-	P	-	-	P	-
M4	P	P	-	-	-	P
M5	P	-	-	-	-	P
M6	-	P	-	-	P	-

Table 5.4 Workstation operation schedule

Workstation	D1				D2				D3				D4				D5			
	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4
W1	Y	Y	Y	N	N	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	N
W2	Y	Y	Y	Y	Y	N	N	Y	Y	N	Y	Y	N	N	Y	Y	Y	Y	Y	N
W3	Y	N	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: "Y" = workstation will be performed, "N"= workstation will not be performed

The example of calculation of total number of all possible satisfaction (*MS*) for D1 *MS* is 27 from the pairs of workers – task preference $\sum_{j=1}^{J}\sum_{k=1}^{K} N_j \times P_{jk}^1$ = 15 and from pairs of team preference $\sum_{j=1}^{J}\sum_{k=1}^{K} N_j \times (N_j - 1) \times p_{jk}^1 ; \text{for } N_j \geq 2$ = 12.

5.2 Optimization solution

The optimization software program called ILOG CPLEX V.12.4 was used to solve the optimal solution for the problems. Frist step, each sub-model was solved separately by CPLEX to determine the desired goal values. The optimal solution of each objective was guaranteed as following (see detail of solution in Appendix B). The max average hazard exposure was 0.7811 using computation time 8,163 seconds. The total person-job fit score was 366 with a computation time of 2.2 seconds. The total number of dissatisfied was 9 convert to number of satisfaction is 135, total number of all possible satisfaction was 144 (80 from task-worker pair and 64 from partner preference pair), with a computation time of 3.3 seconds. These three values (0.7811, 366, 135) were set as *Z**, *TSC**, and *TSF** respectively in LP-metric objective function of multi-objective model for both optimization and GA. The decision weight for each objective is 1 (all equal important weight).

Second step, the LP-metric method was solved for multi-objective consideration. CPLEX yielded an optimal solution with a computation time of 149 seconds. The objective value was 0.1636, the max average hazard was 0.7961, the total person-job fit score was 324, and the number of satisfaction was 131. The work schedule result is shown in table 5.5. An amount of hazard exposure is shown in table 5.6.

Table 5.5 Work schedule from LP-metric CPLEX

Worker	D1				D2				D3			
	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4
M1	-	-	T4	-	-	T4	T4	-	T4	T4	-	-
M2	T3	T3	T3	T3	T3	T5	T5	T3	T5	-	T3	T3
M3	T1	T1	T1	-	-	T1	T1	T1	T1	T1	T1	-
M4	T2	T2	T2	T2	T2	-	-	T2	T2	T5	T2	T2
M5	T4	-	-	-	T4	-	-	T4	-	-	T4	T4
M6	T5	-	T5	-	T5	-	-	T5	T3	-	T5	T5
Worker	D4				D5							
	P1	P2	P3	P4	P1	P2	P3	P4				
M1	-	-	T4	T4	-	-	T4	T4				
M2	T5	-	T3	T3	T3	T3	T5	T5				
M3	T1	T1	T1	-	T1	T1	T1	-				
M4	T4	-	T2	T2	T2	T2	T2	-				
M5	-	T4	-	T1	T4	T4	-	-				
M6	-	T5	T5	T5	T5	T5	T3	-				

Table 5.6 Daily hazard exposures of the six workers from LP-metric CPLEX

Worker	D1	D2	D3	D4	D5	Average	SD
M1	0.4423	0.8846	0.8846	0.8846	0.8846	**0.7961**	0.1978
M2	0.6824	0.9842	0.6627	0.6627	0.9842	0.7952	0.1727
M3	0.7821	0.7821	0.7821	0.7821	0.7821	0.7821	0.0000
M4	0.8876	0.4438	0.9872	0.8861	0.6657	0.7741	0.2189
M5	0.4423	0.8846	0.8846	0.7030	0.8846	0.7598	0.1941
M6	0.6430	0.6430	0.8136	0.9645	0.8136	0.7755	0.1358

Note: The bold face values are the maximum average hazard exposure

Table 5.6 shows daily hazard exposure of the 6 workers for all five workdays (from the LP-metric method). It is clear to see that for each worker, the hazard exposure that one has to endure in each workday is not the same except for M3. For example, worker M4 has to receive rather a large amount in workday D3 (daily hazard exposure = 0.9872) but receive moderately less in workday D2 (daily hazard exposure = 0.4438). The average hazard exposure during the planning period of worker M4 is 0.7741, with a standard deviation of 0.21. Among the 6 workers, worker M1 has the maximum average hazard exposure of 0.7961. Worker M5 has the minimum average hazard exposure of 0.7598. The difference from sub-model optimal solution Z^*, TSC^*, and TSF^* are 1.96%, 11.48%, and 2.96% respectively.

5.3 Genetic algorithm solution

Next, the genetic algorithm approach was employed to determine the solution of each sub-problem. The procedure described in chapter 4 is coded in a MATLAB m-file program based on the GA tool box procedure. GA termination conditions are set according to chapter 4.2.7. It is important to determine suitable GA parameters. From experiment, the optimal control parameters were determined as follows:

1) The population size (Popsize) = 150 chromosomes,
2) The crossover fraction = 0.5, and
3) A maximum number of generation (Max_gen) = 3,000 generations.

To protect from more surplus search in upcoming later generations, the crossover and mutation were not necessary performed in every workday segment of the chromosome. This might help to find a better local solution. The genetic operator will perform all workday segments until reaching 1,000 generations after that only perform for 50% of the workday chosen randomly for the next 1,000 generations. Remaining generations are only performed once workday, chosen randomly.

The termination time was set at 1,000 seconds for all the test problems. Each problem was solved 5 times. The best value for each objective (goal/target value for multi-objective) was determined by optimization software IBM ILOG CPLEX V12.4 and set computation time limit to 12 hours if optimality cannot guarantee.

The best solution from GA of each sub-model was set as the initial solution of LP-metric GA. The GA gave the solution that objective value = 0.1703 (Z=0.7961, TSC=327, and TSF=129). The work schedule result is shown in table 5.7. The amount of hazard exposure is shown in table 5.8.

Table 5.7 Work schedule from LP-metric GA

Worker	D1				D2				D3			
	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4
M1	T4	-	-	-	-	-	T4	T4	-	T4	-	T4
M2	T3	T3	T3	T3	T3	-	T5	T3	T3	T5	T5	T3
M3	T1	T1	T1	-	-	T1	T1	T1	T1	T1	T1	-
M4	T2	T2	T2	T2	T2	-	-	T2	T2	-	T4	T2
M5	T5	-	T4	-	T4	T4	-	-	T4	-	T2	-
M6	-	-	T5	-	T5	T5	-	T5	T5	-	T3	T5
Worker	**D4**				**D5**							
	P1	P2	P3	P4	P1	P2	P3	P4				
M1	-	-	T4	T4	T4	-	-	T4				
M2	-	T5	T5	T3	T3	T3	T3	T5				
M3	T1	T1	-	T1	T1	T1	T1	-				
M4	-	T4	T2	T2	T2	T2	T2	-				
M5	T4	-	T1	-	-	T4	T4	-				
M6	T5	-	T3	T5	T5	T5	T5	-				

Table 5.8 Daily hazard exposures of the six workers from LP-metric GA

Worker	D1	D2	D3	D4	D5	Mean	SD
M1	0.4423	0.8846	0.8846	0.8846	0.8846	**0.7961**	0.1978
M2	0.6824	0.6627	0.9842	0.8136	0.8333	0.7952	0.1302
M3	0.7821	0.7821	0.7821	0.7821	0.7821	0.7821	0.0000
M4	0.8876	0.4438	0.8861	0.8861	0.6657	0.7539	0.1980
M5	0.7638	0.8846	0.6642	0.7030	0.8846	0.7800	0.1018
M6	0.3215	0.9645	0.8136	0.8136	0.9645	0.7755	0.2648

5.4 Comparison of solution

The summary result of both solution approaches presented in table 5.9. The GA LP-metric objective value was different at 4.1% from the optimal value. For each aspect objective value, *Z* was equal for both CPLEX and GA. For *TSC* and *TSF*, GA has 3 and 2 deviation from CPLEX respectively. For sub-model solution, GA was different from the optimal value equaling 0.41%, 0.82%, and 4.44% for *Z*, *TSC*, and *TSF* respectively.

Table 5.9 Summary result from each approach

	LP-metric objective value	*Z*	*TSC*	*TSF*	Computation time (second)
Optimal LP-metric	0.1636	0.7961	324	131	149
GA LP-metric	0.1703	0.7961	327	129	253
Optimal for each sub-model		0.7811	366	135	8163/2.2/3.3
GA for each sub-model*		0.7843	363	129	166/185/223

*see detail of solution in Appendix B

From the numerical example, results of the GA were quite satisfies. It can yield near optimal solution using reasonable computation effort. In the next chapter, the computation experiment will be tested with sets of different sizes of problem to exam efficiently of GA.

Chapter 6
Computation Experiment

6.1 Test Problems

Six hypothetical test problems (P1 – P6) were generated. The number of workers ranged between 6 and 18 persons, the number of work stations ranged between 3 and 7 stations and the number of tasks ranged between 5 and 15 tasks. The planning period was 5 workdays. All test problems considered non-uniform hazard exposure at a workstation. Table 6.1 shows the numbers of workers, work stations and tasks used in each test problem. The worker-task person-job fit scores were randomly generated, with the scores ranging between 1 and 5.

Table 6.1 Six test problems for the computation experiment

Problem	Number of		
	Workers	Workstations	Tasks
P1	6	3	5
P2	7	3	5
P3	10	5	8
P4	11	5	8
P5	13	5	10
P6	18	7	15

6.2 Experiment Design

Two solution approaches (i.e., optimization, GA) were implemented for 6 test problems. The weight for LP-metric set equaled one for all objectives. For the optimization approach, efficient optimization software named IBM ILOG CPLEX v.12.4.0 was used. The MATLAB v.7.11.0.584 with GA Toolbox was utilized to process the GA. The same personal computer was used to solve all test problems for both approaches Computer specifications: Intel Core i5-2500K, 3.0 GHz, 4GB RAM. For GA, each test problem was solved for 5 replicates. The best solution for each objective is shown in table 6.2. The target value Z^*, TSC^*, and TSF^* for main-model LP-metric are set from optimal or best solution from optimization CPLEX. The termination conditions in chapter 4.27 and parameters in chapter 5.3 were used for computation experiment.

For the optimization approach, a few test problems could not be solved to optimality. The computation time limit was set to 12 hours (node files on disk and compress is set to prevent "out of memory" error), if CPLEX cannot reach optimal solution within this time limit, the current best solution would be represented by the upper bound solution.

Table 6.2 Sub-model results for both CPLEX and GA

(a) solution

Problem	CPLEX (optimal)			Genetic Algorithm		
	Z	*TSC*	*TSF*	*Z*	*TSC*	*TSF*
P1	0.7811	366	135	0.7843	363	129
P2	0.7915	396	151	0.7919	391	143
P3	0.8909*	617	239	0.8919	589	215
P4	0.8894*	653	220*	0.8907	627	201
P5	0.8871*	806	380*	0.89	761	334
P6	0.8863*	1271*	640*	0.8963	1191	594

Note: * = best solution (upper bound) when reach time limit

(b) computation time (second)

Problem	CPLEX			Genetic Algorithm		
	Z	*TSC*	*TSF*	*Z*	*TSC*	*TSF*
P1	8,610	2.1	3.3	166	185	233
P2	3,121	1.6	3.1	163	188	234
P3	43,200	2	18	185	208	262
P4	43,200	5.1	43,200	183	210	263
P5	43,200	59	43,200	211	236	307
P6	43,200	43,200	43,200	271	296	398

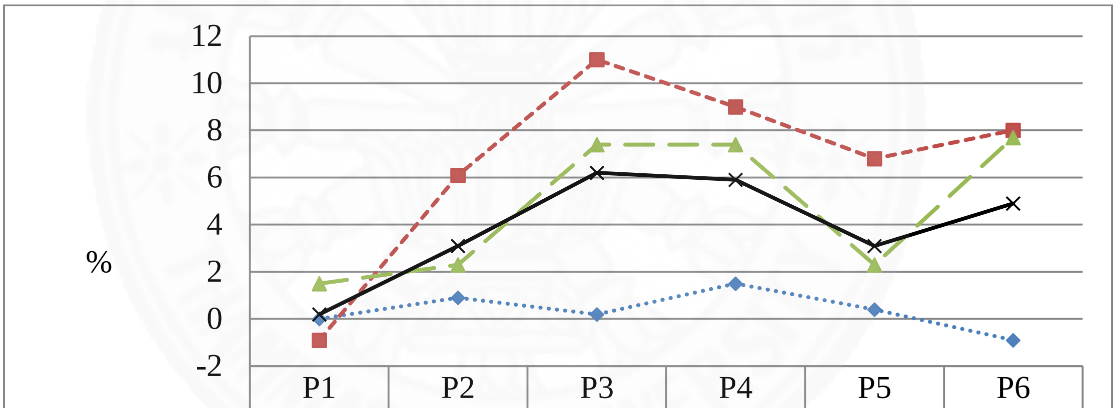
6.3 Results

The LP-metric solutions from two approaches are summarized and shown in Table 6.3. Optimization approach CPLEX and GA are able to find the multi-objective multi-workday ergonomic work schedule solutions with the workers' total hazard exposure amounts did not exceed the permissible limit in all solved test problems. The comparison of the two approached are shown in figure 6.1.

Table 6.3 LP-metric result

Problem	CPLEX					Genetic Algorithm				
	Dev.	*Z*	*TSC*	*TSF*	CT	Dev.	*Z*	*TSC*	*TSF*	CT
P1	0.1636	0.7961	324	131	149	0.1703	0.7961	327	129	253
P2	0.3017*	0.7961	326	133	43200	0.3808	0.803	306	130	248
P3	0.1508*	0.9013	557	229	43200	0.3227	0.9031	496	212	304
P4	0.1416*	0.9024	579	217	43200	0.3089	0.9157	527	201	304
P5	0.2456*	0.9070	694	348	43200	0.3288	0.9104	647	340	344
P6	0.171*	0.9143	1109	625	43200	0.3071	0.9063	1020	577	441

Note: CT is computation time (second). Dev. =deviation (objective value of LP-metric); * = best solution (upper bound) when reach time limit



	P1	P2	P3	P4	P5	P6
Z	0	0.9	0.2	1.5	0.4	-0.9
TSC	-0.9	6.1	11	9	6.8	8
TSF	1.5	2.3	7.4	7.4	2.3	7.7
Average	0.2	3.1	6.2	5.9	3.1	4.9

Figure 6.1 Percent different LP-metric GA/CPLEX

From table 6.2, when solving sub-model *TSC* all test problems guaranteed the optimal solution except P6. But the sub-model *Z* could only guarantee optimal solution for 2 problems (P1 and P2). The three GA sub-models gave a solution when terminated by maximum generation. Table 6.3 shows applying the LP-metric method to 6 test problems. From the CPLEX solution, all test problems obtained only feasible solution after the time limited 12 hours except for P1 that obtained optimal solution. The best GA solution from five replicate are also shown in table 6.3. From figure 6.1, the difference from optimization approach was -0.9 to 1.5 percentages for the percentage for maximum average hazard, -0.9 to 11.0 percentages for the total person-job fit score, and 1.5 to 7.4 percentages for the total number of satisfaction. The average of difference was 0.2 to 6.2 percentages. Solving to each sub-model will result in sacrificing the other aspect objective values. Thus, the LP-metric method could be helped to manage to get a suitable results for multi-objective consideration. The result from LP-metric can obtain a varied results up to the decision, policy or strategy of schedule maker that represented in an important weight of each objective. In this case, defined equal weight will help to employ the trade-off solution between smoothing hazard exposure, total person-job fit score, and total number of satisfaction with equal priority. The genetic algorithm demonstrated good performance with respect to computation time. Even the large size problem P6, it needed less than 5 minutes to obtain the solution. For the same test problem, the optimization CPLEX used 12 hours and could not guarantee the optimal solution. Another advantage, the GA is capable of solving large real world problem sizes with acceptable results as for small size. In the other hand, solving large size NP-hard problem on CPLEX is difficult and using more computation effort. The result will far from an optimal value or even unable to yield any feasible solutions for very large size problem.

Chapter 7
Conclusions and Recommendations

This chapter provides the research conclusion and recommendations of this dissertation. The results of the proposed methods are compared and discussed, which leads to the summary of the research and research conclusion. Keys contributions to both academic research community and industry are presented. Recommendations for further studies are also proposed in the last section.

7.1 Summary of the Research

In this dissertation the application of genetic algorithm for multi-workday ergonomic workforce scheduling problem with complex personal and task constraints was studied. The solution was to develop an extended multi-day rotating work schedule for workers to alleviate their total hazard exposures and prevent them from exceeding the permissible daily limit. The works are heterogeneous in terms of limited skill to conduct the job or task. Additionally, workstation operation schedules were concerned because a few workstation might need to stop at a period for any unforeseen situation (i.e., maintenance, inspection, change part). To generate the work schedules, three related criteria were described: (1) workers hazard exposure balancing, (2) productivity, and (3) satisfaction. The first objective was hazard exposure balancing, as general ergonomic WSP only consider single day schedules. In order to apply this for several days, the schedule might be the same (hazard dose and task requirement are not change) that can impact on hazard exposure balancing among workers. If a few workers are exposed the amount of hazard more than another, its can affect satisfaction, health and worker morale. The second objective was productivity evaluate by fit of the person-job score because job rotation can affect productivity when rotating worker to the incompetence task. Another objective was satisfaction of workers which can help to enhance performance of a work and reduce turnover rate. The goal of this research was to develop a genetic algorithm approach and combine the LP-metric method to determine a solution with multi-objective consideration.

The multi-workday ergonomic WSP can be formulated as a mathematical model and expressed as a mixed integer programming model (MILP). The model was split into three sub-models as a single objective model and one multi-objective LP-metric method model. The optimization software such as the IBM ILOG CPLEX V.12.4.0 was employed to solve the problem optimality. One of the objectives was to consider this as *NP-hard problem*. Thus, it was difficult the for an optimization approach to reach optimal solution in a suitable computation time. A genetic algorithm coding in MATLAB v.7.11.0.584 m-file base on GA optimization tool box was developed to solve the problem. The encoding method used permutation encoding that was suitable for combinatorial optimization problem. Moreover, the proposed modified crossover and mutation were employed which was more efficient than conventional GA operators. To verify the efficiency of proposed GA, six test problems were generated. The computation experiment showed that each sub-model would result in designs in which one aspect was sacrificed for another. Solving the multi-objective model by the LP-metric method can makes a tradeoff for the productivity and hazard exposure balancing among workers for a policy that allowed definition of important weight for each objective. For the efficiency, the results show that GA could reach a near optimal solution with a reasonable computation time. The solution from LP-metric provided a perfect solution between hazard exposure balancing, person-job fit score, and workers satisfaction.

In conclusion, the proposed multi-objective multi-workday workforce scheduling model was able to find the optimal solution for multi-workday ergonomic workforce scheduling with personal and task constraint for small size problems. The genetic algorithm can be employed to both solve small and large-sized problems. The genetic algorithm provided the near optimal solutions within a reasonable computation time. The daily rotating work schedule solution achieved the safety/ergonomics, productivity, and satisfaction goals. That is, the genetic algorithm was a good alternative method to deal with multi-workday ergonomic workforce scheduling with personal and task constraints and can be implemented in a variety of environment systems (i.e., service, manufacturing, transportation).

7.2 Key Contribution of the Research

The proposed multi-objective multi-workday workforce scheduling model includes three outstanding characteristics. First, the ergonomic, productivity, and satisfaction are taken into account in this combination. The aim is to obtain a suitable tradeoff solution for three objectives (hazard balancing, productivity, satisfaction) simultaneously under complex constraints in hazard exposure, personal and worker-task requirements. Second, job rotation can be achieved in workforce scheduling by considering daily rotation. The hazard exposure amount is evaluated in a quantitative approach for monitoring and controlling. And third, realistic constraints in hazard exposure, personal, and workstation-task are covered. Under these unique points, this research is expected to provide exclusive contributions to both the academic community and manufacturing.

7.2.1 Contribution to academic community

Multi-workday ergonomic workforce scheduling with personal and task constraint addressed in this dissertation is expected to provide wide contribution to the academic community, especially in the fields of operation research for applications, safety and health care management, and engineering management etc. The examples of contribution to the academic community are:

<u>Safety and health care management:</u>

- Safety aspect can be achieved simultaneously with productivity and job satisfaction considerations.
- The daily hazard exposure of operators can be effectively controlled by measuring in quantitative amount and applying operation research methods to obtain the best solution.

<u>Operations research in applications:</u>

- The optimization and genetic algorithm methods can be applied to determine the optimal or near optimal solution in even qualitative aspect such as workers' safety consideration and job/team satisfaction.
- This research study can determine as an example of the problem including conflict of objectives which could be achieved simultaneously with a weighted decision under the complex constraints.

- Mathematical model for the multi-workday ergonomic workforce scheduling with personal and task constraint are provided.
- The limitation when solving the large-complex combinatorial optimization problem by using optimization techniques is proved for characteristics of *NP-hard* problems.
- The genetic algorithm approach for multi-workday ergonomic workforce scheduling problem is proposed.
- Advantages and disadvantages of both optimization and genetic algorithm approach are presented in the comparison.

Engineering management:

- Satisfaction and ergonomic consideration can be simultaneously achieved with the high total system productivity under complex worker and tasks constraints.
- Applying optimization techniques and a genetic algorithm according to this research is a good alternative way to deal with multi-workday workforce scheduling, which is a *NP-hard* problem, under complex constraints.

7.2.2 Contribution to industry

This research aimed to provide contributions to the industrial applications in many ways such as:

- Ergonomic and satisfaction aspect are taken into account more as ones of the importance factors when constructing an effective worker-task schedule.
- Combination of ergonomic and satisfaction to the achievement of high total system productivity can be implemented to real circumstances by using the proposed multi-objective model in this research.
- Workers gain more satisfactions in their works due to the safe working condition, task preference, and partner preference.
- Industry organizations obtain effective multi-workday ergonomic workforce schedule procedures which confirm to have less fluctuate in hazard exposure among workers, the highest total system productivity (in total person-job fit score), and workers' satisfactions (in task and partner preferences) at the same time.
- The proposed genetic algorithm is a good alternative method to deal with realistic size of multi-workday workforce scheduling problems.

7.3 Recommendation for Further Studies

For future study in multi-workday workforce scheduling problems, one is recommended to focus on these following issues:

- Extended planning period that covers a longer period (e.g. weekly, monthly) would be of interest to consider in further research.
- A few more realistic constraints in both workers and workstations might be considered. Workers constraints: day-off, restrict workday, worker regulation and variable-limit hazard exposure. Workstations constraints: variable work-period durations.
- Find more multi-objective methods for choice of decision.
- Determine solutions from other interesting approaches such as heuristic and metaheuristic and test efficiently with a genetic algorithm.

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Appendices

Appendix A
Application of MW-EWSP in the VRPMMH

The Appendix A presents application of multi-workday workforce scheduling problems in vehicle routing problem with manual materials handling (VRPMMH) that is multi-workday vehicle routing problem (MW-VRP). First, the problem description is clarified and two policies for assign worker to delivery vehicle are proposed. The optimization approach and comparison of policies for MW-VRP was published in Rattanamanee et al., (2015). Then, the mathematical model and heuristic procedure approaches are implemented. The numerical results are shown for comparison. The computation experiment is examined.

1. Problem Description

MW-VRP involves a logistics system with one supplier and a set of customers. Goods have to be delivered to the customers on a daily basis. A planning period consists of several consecutive workdays. The supplier has a set of delivery vehicles which have limited load capacities. Each vehicle has one driver and a team of delivery workers. The unloading of goods at customer locations are performed only by the worker team. The size of worker team (i.e., the number of workers per team) usually depends on the vehicle size. Irrespective of the vehicle's daily carried loads, the required number of workers accompanying the vehicle is unchanged. Delivery workers are heterogeneous with respect to their working energy capacities. Each day, the vehicles depart from the supplier, visit their assigned customers, perform the delivery to satisfy the daily customer demands, and return to the supplier when all of their assigned customers have been visited. All vehicles perform only one delivery trip per one 8-hour workday.

Each customer requires a certain quantity of goods to be delivered every workday during the given planning period. For any customer, its daily demands do not have to be the same. The customer demands of all workdays are known in advance at the beginning of the planning period. When the vehicle arrives at the customer location, the worker team unloads the goods from the vehicle and move them into a stock room. All load handling activities at the customer location are performed manually, possibly with the use of hand carts or dollies. All workers in the team are assumed to split the goods to be unloaded equally irrespective of their working energy capacities.

MW-VRP must satisfy the following conditions:

1. The vehicle must not carry goods more than its load capacity.
2. All vehicles must be utilized in each workday.
3. The customer must receive its daily demand only once per day and from only one vehicle.
4. Each day, the daily total energy expenditure of the worker must not exceed his/her working energy capacity.

For each vehicle, while the size of worker team is fixed every workday, the daily worker-vehicle pairings can be either fixed or varied. When the worker-vehicle pairings are fixed, workers are said to be “pre-assigned” to vehicles at the beginning of the planning period. Further, the same worker-vehicle pairings are applied every workday throughout the planning period. Note that the assignment of workers to vehicles is performed before knowing the delivery routes of the vehicles and, subsequently, their carried loads in each day.

When the daily worker-vehicle pairings are varied, it means that a worker might be assigned to one vehicle in one day and then assigned to another vehicle (either with the same or different partner(s)) in another day. It is then assumed that workers are “post-assigned” to vehicles after knowing how much load each vehicle must carry each day. To know the carried load of a vehicle, it is necessary to know which customers are to be served by that vehicle.

To unload one unit of goods from the vehicle, the worker has to expend a certain amount of his/her energy. Since the workers are heterogeneous, their working energy capacities are unequal. A physically fit person is said to have a large amount of working energy capacity while a weak person has a small amount. The daily total energy expenditure of a person is the sum of one’s physical energies expended at all customer locations where one unloads the goods. At the end of the workday, a residual energy of the worker can be calculated as a difference between one’s working energy capacity and one’s daily total energy expenditure. For any workday, if the worker's residual energy is small, it implies that the worker's workload is heavy. On the other hand, if the residual energy is large, the worker's workload is light. For further explanation on working energy capacity and energy expenditure, see Boonprasurt and Nanthavanij (2012).

MW-VRP with ergonomic consideration of physical workload is intended to determine the delivery routes of all vehicles for each workday during the planning period such that all workers share relatively equal physical workloads during that period. Two policies of worker-vehicle pairing are evaluated:

1. Worker-vehicle pre-assignment policy
2. Worker-vehicle post-assignment policy

2. Mathematical Models

The mathematical formulation of MW-VRP is based on the following assumptions.

1. The worker's working energy capacity is known.
2. The average rate of energy expenditure to unload a unit of goods is known and constant.
3. The energy capacity of the vehicle is the sum of working energy capacities of the workers (excluding a driver) assigned to the vehicle.
4. All delivery workers in the same vehicle split the goods to be unloaded equally.
5. The vehicle's load capacity is known.
6. Daily customer demands during the planning period are known in advance.

2.1 Worker-vehicle pre-assignment policy

According to this policy, workers are pre-assigned to vehicles and the worker-vehicle pairings are fixed throughout the planning period. As a result, the energy capacities of the vehicles are known in advance. The daily delivery routes of all vehicles can then be determined with an objective to minimize the maximum average percent residual energy among workers as computed over the planning period. This objective will help to yield the MW-VRP solution where all workers receive relatively equal physical workloads on average during the planning period.

The notation used in the formulation of the mathematical model is as follows:

Parameters:

AE average energy expenditure (kcal/unit) for a worker to unload one unit of goods

C_k load capacity (units) of vehicle k

d_{ij} distance (km) from node i to node j

D_j^t demand of customer j (units) in workday t

EC_{kl} working energy capacity (kcal/day) of worker l assigned to vehicle k

K number of vehicles; $k \in \{1,\ldots,K\}$

N number of customers including a supplier; $i, j \in \{1,\ldots,N\}$; 1 = supplier

T number of workdays in a planning period; $t \in \{1,\ldots,T\}$

W_k number of workers assigned to vehicle k; $l \in \{1,\ldots,W_k\}$

Variables:

AVG maximum average percent residual energy among workers as computed over the planning period

PE_{kl}^t fraction of the working energy capacity of worker l assigned to vehicle k spent in workday t

U_i^t variables used to avoid sub tours, and can be interpreted as the position of node i along the route in workday t

Decision variables:

$$X_{ijk}^t = \begin{cases} 1 & \text{if vehicle } k \text{ travels from node } i \text{ to node } j \text{ in workday } t \\ 0 & \text{otherwise} \end{cases}$$

$$Y_{jk}^t = \begin{cases} 1 & \text{if vehicle } k \text{ travels to node } j \text{ in workday } t \\ 0 & \text{otherwise} \end{cases}$$

MW-VRP with the worker-vehicle pre-assignment policy can be described as follows.

$$\text{Minimize} \quad AVG \tag{1}$$

subject to

$$U_j^t \geq U_i^t + 1 - N(1 - \sum_{k=1}^{K} X_{ijk}^t) \qquad i, j = 2,...,N; i \neq j;\ t \in T \qquad (2)$$

$$\sum_{i=1}^{N} X_{ihk}^t - \sum_{j=1}^{N} X_{hjk}^t = 0 \qquad h = 2,\ldots,N;\ k \in K \qquad (3)$$

$$\sum_{i=1}^{N} X_{ijk}^t = Y_{jk}^t \qquad j = 2,\ldots,N;\ k \in K;\ t \in T;\ i \neq j \qquad (4)$$

$$\sum_{k=1}^{K} Y_{jk}^t = 1 \qquad j = 2,\ldots,N;\ t \in T \qquad (5)$$

$$\sum_{j=2}^{N} X_{1jk}^t = 1 \qquad k \in K;\ t \in T \qquad (6)$$

$$\sum_{j=2}^{N} Y_{jk}^t D_j^t \leq C_k \qquad k \in K;\ t \in \qquad (7)$$

$$\frac{AE \cdot \sum_{j=2}^{N} Y_{jk}^t D_j^t}{W_k \cdot EC_{kl}} = PE_{kl}^t \qquad l \in W_k;\ k \in K;\ t \in T \qquad (8)$$

$$\frac{\sum_{t=1}^{T} \left(1 - PE_{kl}^t\right)}{T} \leq AVG \qquad l \in W_k;\ k \in K \qquad (9)$$

$$PE_{kl}^t \leq 1 \qquad l \in W_k;\ k \in K;\ t \in T \qquad (10)$$

$$X_{ijk}^t \in \{0,1\}, Y_{jk}^t \in \{0,1\} \qquad i, j \in N;\ l \in W_k;\ k \in K;\ t \in T \qquad (11)$$

Objective function (1) is intended to minimize the maximum average percent residual energy among workers during the planning period. Constraint (2) prevents the sub-tour formation. Constraint (3) guarantees that at each customer location, the vehicle that arrives must also leave the location. Constraints (4) and (5) state that each customer is visited by only one vehicle in each workday and all customers must be served. Constraint (6) states that all vehicles must be utilized in each workday. Constraint (7) requires that the vehicle cannot carry loads beyond its capacity. Constraint (8) computes the energy expenditure as a fraction of the worker's working energy capacity. Constraint (9) requires that the average percent residual energy among workers over the planning period must not exceed the maximum average (or the upper bound). Constraint (10) ensures that the fraction of the worker's working energy capacity does not exceed 1. Finally, constraint (11) defines binary decision variables.

To improve the routing solution, we employ another mathematical model to minimize the total travel distance for all vehicles while using the optimal average percent residual energies of individual workers as constraints. New variables and parameters are defined as follows:

A_{kl} optimal average percent residual energy of worker l who is assigned to vehicle k

TD total travel distance of all vehicles during the delivery period

Objective function (1) is replaced by objective function (12) since the model is intended to minimize the total travel distance for all vehicles.

$$\text{Minimize} \quad TD = \sum_{t=1}^{T}\sum_{j=1}^{N}\sum_{i=1}^{N}\sum_{k=1}^{K} X_{ijk}^{t} d_{ij} \tag{12}$$

Next, constraint (9) is removed from the model and constraint (13) is inserted. This constraints states that any new delivery routes must not increase the optimal average percent residual energy of worker l who is assigned to vehicle k, A_{kl}, that is obtained from the first MW-VRP model

$$\frac{\sum_{t=1}^{T}\left(1-PE_{kl}^{t}\right)}{T} \le A_{kl} \qquad l \in W_k;\ k \in K \tag{13}$$

2.2 Worker-vehicle post-assignment policy

Based on this policy, workers are assigned to vehicles only after knowing the carried loads of individual vehicles in each workday. Firstly, a minimum-distance VRP model is utilized to determine the optimal delivery routes of all vehicles. The model is applied separately for each workday during the planning period. Not knowing the worker-vehicle pairings, the exact energy capacities of vehicles are not known at the beginning of the planning period. There is a possibility that some large vehicles could be assigned to serve too many customers in one workday to reduce the total travel distance. When workers are later assigned to the vehicles, they might have to work beyond their working energy capacities. To prevent this situation, an average working energy capacity is computed from all workers. It is then applied as a representative working energy capacity of one worker to estimate the vehicles' energy capacities.

Once the optimal delivery routes in each workday are known, the carried loads of individual vehicles can be determined (by summing the demands of all served customers) throughout the planning period. Then, workers are assigned to vehicles such that the maximum average percent residual energy among all workers during the planning period is minimized.

Two mathematical models are sequentially solved. The first model is intended to find the minimum-distance delivery routes of all vehicles in each workday based on the actual daily customer demands. Next, the second model is applied to determine the worker-vehicle pairings that optimally allocate physical workloads among the workers during the planning period.

2.2.1 Optimal delivery routes

Additional parameters, variables, and decision variables are defined as follows:

Parameters:

D_j demand (units) of customer *j* in any given workday

VE average working energy capacity (kcal/day)

Variables:

TD total travel distance in any given workday

U_i variables used to avoid sub tours, can be interpreted as position of node *i*

Decision variables:

$$X_{ijk} = \begin{cases} 1 & \text{if vehicle } k \text{ travels from node } i \text{ to node } j \text{ in any given workday} \\ 0 & \text{otherwise} \end{cases}$$

$$Y_{jk} = \begin{cases} 1 & \text{if vehicle } k \text{ serves customer } j \text{ in any given workday} \\ 0 & \text{otherwise} \end{cases}$$

The minimum-distance VRP model is described below.

$$\text{Minimize } TD = \sum_{k=1}^{K} \sum_{j=1}^{N} \sum_{i=1}^{N} X_{ijk} d_{ij} \tag{14}$$

subject to

$$U_j \geq U_i + 1 - N(1 - \sum_{k=1}^{K} X_{ijk}) \qquad i, j = 2,...,N; i \neq j \qquad (15)$$

$$\sum_{i=1}^{N} X_{ihk} - \sum_{j=1}^{N} X_{hjk} = 0 \qquad h = 2,\ldots,N; k \in K \qquad (16)$$

$$\sum_{i=1}^{N} X_{ijk} = Y_{jk} \qquad j = 2,\ldots,N; k \in K; i \neq j \qquad (17)$$

$$\sum_{k=1}^{K} Y_{jk} = 1 \qquad j = 2,\ldots,N \qquad (18)$$

$$\sum_{j=2}^{N} X_{1jk} = 1 \qquad k \in K \qquad (19)$$

$$\sum_{j=2}^{N} Y_{jk} D_j \leq C_k \qquad k \in K \qquad (20)$$

$$AE \cdot \sum_{j=2}^{N} Y_{jk} D_j \leq W_k \cdot VE \qquad k \in K \qquad (21)$$

$$X_{ijk} \in \{0,1\}, Y_{jk} \in \{0,1\} \qquad i, j \in N; k \in K \qquad (22)$$

Objective function (14) is intended to minimize the total travel distance in any given workday. Constraint (15) ensures sub-tour elimination. Constraint (16) represents the flow conservation. That is, the vehicle that arrives at one customer location must also leave that customer location. Constraints (17) and (18) state that the customer will be visited by only one vehicle and all customers must be served. Constraint (19) requires that all vehicles must be utilized. Constraint (20) prohibits any vehicle from carrying the goods beyond its load capacity. Also, constraint (21) prevents the daily total energy expenditure of any vehicle from exceeding its energy capacity. Finally, constraint (22) defines binary decision variables.

2.2.2 Physical workload balancing

When the delivery routes of all vehicles are known, the required energy expenditure can be determined for each vehicle. Since it is assumed that all team members will split their work (i.e., goods to be unloaded) equally, the required energy expenditure of each worker can be obtained. The mathematical model for physical workload balancing requires the following additional parameters, variables, and decision variables.

Parameters:

EC_l working energy capacity (kcal/day) of worker l

L number of available workers; $l \in \{1,\ldots,L\}$

Q_k^t carried load (units) of vehicle k in workday t

Variables:

AVG maximum average percent residual energy among all workers as computed over the planning period

PE_l^t fraction of the working energy capacity of worker l spent in workday t

Decision variables:

$$P_{lk}^t = \begin{cases} 1 & \text{if worker } l \text{ is assigned to vehicle } k \text{ in workday } t \\ 0 & \text{otherwise} \end{cases}$$

The assignment of workers to vehicles is based on the following assignment model.

$$\text{Minimize } AVG \tag{23}$$

subject to

$$\sum_{l=1}^{L} P_{lk}^t = W_k \qquad k \in K;\ t \in T \tag{24}$$

$$\sum_{k=1}^{K} P_{lk}^t = 1 \qquad l \in L;\ t \in T \tag{25}$$

$$\sum_{k=1}^{M} \left(P_{lk}^t \cdot \frac{AE \cdot Q_k^t}{W_k \cdot EC_l}\right) = PE_l^t \qquad l \in L;\ t \in T \tag{26}$$

$$\frac{\sum_{t=1}^{T}\left(1 - PE_l^t\right)}{T} \le AVG \qquad l \in L \tag{27}$$

$$PE_l^t \le 1 \qquad l \in L;\ t \in T \tag{28}$$

$$P_{lk}^t \in \{0,1\} \qquad l \in L;\ k \in K;\ t \in T \tag{29}$$

Objective function (23) is intended to minimize the maximum average percent residual energy among all workers during the planning period. Constraint (24) requires that each vehicle must be accompanied by the worker team according to its required number of workers. Constraint (25) states that a worker can be assigned to only one vehicle in each workday. Constraint (26) computes the energy expenditure as a fraction of the working energy capacity. Constraint (27) requires that the average percent residual energy among all workers during the planning period must not exceed the maximum value. Constraint (28) states that the fraction of the worker's working energy capacity must not exceed 1. Finally, constraint (29) defines binary decision variables.

3. Heuristic procedure

The MW-VRP is considered to be a combined vehicle routing problem (VRP) and scheduling problem. Since both of problems are well-known *NP*-hard problems, so is the MW-VRP. A heuristic procedure is developed to determine near-optimal delivery routes for all utilized vehicles in each workday during the delivery period whereas the average percent residual energies of individual workers are relatively equal. The following variables and parameters are additionally defined for the development of the heuristic algorithms.

CS_j 1 if customer j is assigned to any vehicle; 0 otherwise

I_k number of customers assigned to vehicle k

L_k^t current carried load (units) of vehicle k in day t

RE_{kl}^t current fractional residual energy (kcal/day) of worker l who is assigned to vehicle k in day t

SD standard deviation of average fractional residual energy (kcal/day)

Z maximum average fractional residual energy (kcal/day) among workers

3.1 Heuristic pre-assignment

The procedure consists of two phases. Firstly, customers are assigned to vehicles to generate vehicle routes. Secondly, the routes are improved using a greedy exchange algorithm to reduce the maximum average fractional residual energy among all workers.

Initialization

0.1 Compute the vehicle's energy capacity $\sum_{l=1}^{W_k} EC_{kl}$ for all k's.

0.2 List all customers in descending order of D_j^t where j = 1 to J for all t's.

0.3 Set $RE_{kl}^t = 1$ for all k's, l's, and t's.

0.4 Set $L_k^t = 0$ for all k's and t's.

0.5 List all vehicles in descending order of the vehicle's energy capacity.

0.6 Set t = 1 and j = 1.

Phase I: Developing vehicle routes

1.1 List all vehicles in descending order of the maximum RE_{kl}^t. In case of having a tie, break the tie by following the list in step 0.5. Choose the first vehicle k on the list (set k=1).

1.2 If $L_k^t + D_j^t \le C_k$ and $RE_{kl}^t - \frac{AE \cdot D_j^t}{W_k \cdot EC_{kl}} \ge 0$ for all k's and l's, assign customer j to vehicle k. Update L_k^t and RE_{kl}^t. Include customer j in the vehicle k's route. Then, proceed to the step 1.3.

If any or all of the above conditions are not satisfied, set $k = k + 1$. Repeat step 1.2. If $k > K$, clear all the assignment of customers and vehicle routes in this day t and use follows algorithm instead:

1.2.1 Set k = 1 (alternating large and small vehicles as sequence order), j = 1 and $CS_j = 0$ for all j's.

1.2.2 If $CS_j = 0$, proceed to the next step. Otherwise, go to step 1.2.4.

1.2.3 If $L_k^t + D_j^t \le C_k$ and $RE_{kl}^t - \frac{AE \cdot D_j^t}{W_k \cdot EC_{kl}} \ge 0$ for all k's and l's, assign customer j in the vehicle k's route and set $CS_j = 1$. Update L_k and RE_{kl}^t, and proceed to the next step.

1.2.4 Set $j = j + 1$. If $j \le J$, return to step 1.2.2. Otherwise, proceed to the next step.

1.2.5 If $CS_j = 1$ for all j's, proceed to the step 1.4. Otherwise, set j = 1 and $k = k + 1$. Return to step 1.2.2.

1.3 Set $j = j + 1$. If $j \leq J$, return to step 1.1. Otherwise, re-compute/update Z and SD. Then, proceed to the next step.

1.4 Set $t = t + 1$ and $j = 1$. If $t \leq T$, return to step 1.1. Otherwise, set $t = 1$ and proceed to *Phase II*.

Phase II: Improving vehicle routes by reducing Z and *SD*

2.1 Set $k = 1$ (where $k \in K$), $i = 1$ (where $i \in I_k$), $m = 1$ (where $m \in K$), and $n = 1$ (where $n \in I_m$).

2.2 Set customer n of vehicle m in day t as $PC(m, n, t)$.

2.3 Set $k = k + 1$. If $k > K$, go to step 2.6. Otherwise, set customer i of vehicle k in day t as $SC(k, i, t)$.

2.4 If $L_m^t - D^t(PC) + D^t(SC) \leq C_m$ and $L_k^t + D^t(PC) - D^t(SC) \leq C_k$, simulate exchange between customer PC in vehicle m's route and customer SC in vehicle k's route and compute new RE_{kl}^t, new Z, and new SD proceed to the next step.

Otherwise set $i = i + 1$. If $i \leq I_k$, set customer i as SC. Repeat this step. If $i > I_k$, return to step 2.3.

2.5 If new $RE_{kl}^t > 0$ and the new Z does not exceed the current Z (in a case that the new Z equals the current Z, the new SD must be less than the current SD), exchange between customer PC in vehicle m's route and customer SC in vehicle k's route. Update RE_{kl}^t, L_k^t, Z, and SD. Then, return to step 2.1.

Otherwise, set $i = i + 1$. If $i \leq I_k$, set customer i as SC and return to step 2.4. If $i > I_k$, return to step 2.3.

2.6 Set $n = n + 1$. If $n > I_m$, proceed to the next step. Otherwise, set $k = m$ and return to step 2.2.

2.7 Set $m = m + 1$ and $n = 1$. If $m > K$, proceed to the next step. Otherwise, set $k = m$ and return to step 2.2.

2.8 Set $t = t + 1$. If $t > T$, proceed to the next step. Otherwise, return to step 2.1.

2.9 Repeat *Phase II* until Z cannot be decreased any further. Then, proceed to the next step.

2.10 Optimize each route using the 2-opt edge exchange. Record a new total travel distance.

3.2 Heuristic post-assignment

Frist, a minimum travel distance of vehicles are determined in section 3.2.1. Then, algorithms for post-assignment are also developed to obtain balancing workload worker-vehicle paring in section 3.2.2.

3.2.1 Determine a minimum total travel distance

This section, the sweep nearest algorithm (SWNA) (Na et al., 2011) is applied for this problem. The SWNA improve from original sweep algorithm by using nearest neighborhood search and multi reference point. The vehicle's energy capacity constraint is considered in this problem. In order to determine delivery routes all workday, the heuristics need to utilize each workday separately with daily demand of customers.

PHASE I: The SWNA for construct routes

Step0: Set stop i=1 as reference point, use *VE* to compute the energy capacity of vehicle.

Step1: Calculate the polar angle between each stop and the reference point.

Step2: Sort stops in increasing order of polar angle (counter-clockwise direction): $S_{1,\ldots,}S_n$; Set number of random equal K×10.

Step3: Random vehicles as permutation random. Set k=1.

Step4: Choose vehicle k. Assign the unrouted stop with the smallest polar angle to the vehicle k.

Step5: Select the nearest stop from the current route. Continue to assign such a nearest stop to the vehicle and construct a route while the sum of demand does not exceed the capacity of the vehicle and the sum of energy expenditure does not exceed the energy capacity of vehicle.

Step6: If an unrouted stop exists (unassigned customer(s) remaining), set k=k+1, go to step4. If k>K set this solution as an infeasible solution go to step8.

Otherwise (all customers are assigned), if all vehicles are utilized, proceed to step7; otherwise set this solution as an infeasible solution and go to step8.

Step7: Optimize each route using 2-opt edge exchange. Record a solution.

Step8: Repeat Step3–Step7 until reach number of random.

Step9: Repeat Step3–Step8 with sort stops in the decreasing order of the polar angles (clockwise direction).

Step10: Return the best solution (minimum travel distance) from record solutions.

Step11: Set i=i+1 as next reference point go to step 1. If $i > N$ proceed to step12.

Step12: Return the solution with minimum travel distance (*TD*) and proceed to *Phase II*.

PHASE II: Greedy Exchange Algorithm for reduce total travel distance

Step1: set k=1 to K. i=1 to I_k; set i=1, n=1, k=1, m=1.

m and n is a dummy index same as k and i.

Step2: select customer n of vehicle m as $PC(m,n)$.

Step3: set k=k+1, if $k > K$ go to step6; if $k \le K$, set customer i=1 of vehicle k as $SC(k,i)$.

Step4: check If swap *PC* with *SC* is possible ($L_m - D(PC) + D(SC) \le C_m$ and $L_k + D(PC) - D(SC) \le C_k$), proceed to next step. Otherwise set i=i+1; if $i \le I_k$ set customer i as *SC*, repeat this step. If $i > I_k$ go to step3.

Step5: check If swap *PC* with *SC*, can reduce total travel distance *TD* and energy expenditure does not exceed vehicle's energy capacity; exchange customer *PC* with *SC* in the route of vehicle k and m, update solution. Go to step 1.

Otherwise set i=i+1; if $i \le I_k$ set customer i as SC, go to step4. if $i > I_k$ go to step3.

Step6: set n=n+1, if $n > I_m$ proceed to next step. if $n \le I_m$, set k=m go to step2.

Step7: set m=m+1, n=1. If $m > K$ proceed to next step. If $m \le K$, set k=m go to step2.

Step8: Return *TD*, route and carried loads of vehicles.

3.2.2 Determine delivery workers schedules (vehicle-worker pairing)

Based on carried loads of vehicles from result of section 3.2.1, the objective of this section is to construct multi-workday assignment to balance physical workload among workers during multi-workday deliveries period.

Initialization:

0.1 list the concerned delivery workers in decreasing order of EC_l; l = 1 to L

0.2 list the vehicle in decreasing order of loading quantity Q_k^t for all day t; where k=1 to K

0.3 Initially, set RE_l^t = 1 for all l's, t's.

0.4 set t=1, k=1, l=1.

PHASE I: assign delivery workers to vehicles

Step1: check, if worker l available, proceed to next step. Otherwise select l=l+1, repeat this step.

Step2: check, if vehicle k satisfies required number of workers W_k, set k=k+1 then go to step4. Otherwise proceed to next step.

Step3: check, if $\frac{AE \cdot Q_k^t}{W_k \cdot EC_l} \leq 1$, then assign worker l to vehicle k and set l=l+1; otherwise set l=l+1. Next, go to step1.

Step4: If $k \leq K$, set l=1 go to step1. Otherwise ($k>K$) set t=t+1 proceed to next step.

Step5: If $t \leq T$, set k=1, l=1 go to step1. Otherwise ($t>T$) proceed to next step.

Step6: obtain the initial assignment, calculated Z and SD (standard deviation of average residual among worker), set t=1. Go to *phase II*.

PHASE II: Improve balancing by exchange delivery workers among vehicles

Step1: set k,m=1 to K, i,n=1 to $W_{k/m}$ (i as worker assigned on vehicle k). Set k=1, i=1, n=1, m=1.

Step2: select worker i of vehicle k in day t as $PW(k,i,t)$.

Step3: set m=m+1, if $m>K$ go to step5; if $m \leq K$, set worker n=1 of vehicle m as $SW(m,n,t)$.

Step4: check, if exchange PW with SW, a new RE_l^t can reduce Z or reduce SD; subject to RE_l^t >0, and a new $Z \leq Z$; exchange worker PW with SW in the vehicle k and m, update RE_l^t, Z and SD. Go to step1. Otherwise set n=n+1; if $n \leq W_m$ set worker n as SW, repeat this step. if $n > W_m$ go to step3.

Step5: set i=i+1, if $i > W_k$ proceed to next step. if $i \leq W_k$, set m=k go to step2.

Step6: set k=k+1, i=1. If $k > K$ proceed to next step. If $k \leq K$, set m=k go to step2.

Step7: set t=t+1, if $t \leq T$, go to step1. If $t > T$, proceed to next step.

Step8: update RE_l^t, Z and SD. Repeat *phase II* again until Z can't reduce any more.

4. Numerical Example

Consider a logistics network with one supplier (S) and ten customers (C1 to C10). The delivery period consists of six consecutive workdays (D1 to D6). The supplier has four delivery vehicles (V1 to V4) and ten workers (W1 to W10) who will accompany the vehicles to deliver the goods. The vehicle data is shown in Table 1. All customers are served every workday. Daily customer demands are known in advance and will not be changed. Table 2 shows all daily customer demands during the delivery period. Table 3 shows workers data.

Table 4 shows travel distances between the supplier and all customers, and among all customers. It is assumed that between any two points *x* and *y* in the logistics network, the travel distances from point *x* to point *y* and from point *y* to point *x* are both equal. It is assumed that an average energy expenditure required to unload one unit of load from the vehicle is 30 kcal per unit.

Table 1. Vehicle data

Vehicle	Load Capacity (units)	Delivery Workers
V1	200	3
V2	200	3
V3	100	2
V4	100	2

Table 2. Customer demands (units) during the delivery period

Customer	Workday					
	D1	D2	D3	D4	D5	D6
C1	28	32	29	85	40	63
C2	26	37	90	35	44	41
C3	73	59	37	48	66	45
C4	36	49	81	20	36	39
C5	27	64	50	84	88	46
C6	63	51	104	31	38	57
C7	53	45	43	41	43	68
C8	41	81	34	70	54	51
C9	71	55	46	62	85	26
C10	105	42	33	26	35	46

Table 3. Data of workers

Worker	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10
EC	2500	3000	3000	2500	3000	2500	2500	2000	2500	2500

Note: EC is the working energy capacity of worker

Table 4. Travel distances (km) between supplier and customers and among customers

	S	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
S	0	11	15	20	14	15	9	13	7	18	8
C1	11	0	26	27	5	22	16	24	8	29	17
C2	15	26	0	21	29	24	24	4	18	3	9
C3	20	27	21	0	22	5	11	17	27	22	12
C4	14	5	29	22	0	17	11	27	11	32	20
C5	15	22	24	5	17	0	6	22	22	27	15
C6	9	16	24	11	11	6	0	22	16	27	15
C7	13	24	4	17	27	22	22	0	16	5	7
C8	7	8	18	27	11	22	16	16	0	21	15
C9	18	29	3	22	32	27	27	5	21	0	12
C10	8	17	9	12	20	15	15	7	15	12	0

4.1 Pre-assignment policy

For pre-assignment policy, these workers have already been pre-assigned to vehicles. The worker-vehicle assignments are fixed throughout the delivery period. For convenience, we assign workers W1, W2, and W3 to vehicle V1; workers W4, W5, and W6 to vehicle V2; workers W7 and W8 to vehicle V3; workers W9 and W10 to vehicle V4. Two solution approaches are employed to obtain the MW-VRP solution.

4.1.1 Optimization approach

The logistics problem in the given example is formulated as two MW-VRP models (as described in Section 2). Both models are successively solved using the ILOG CPLEX V.12.4 program. The first model is solved with an objective to minimize the maximum average percent residual energy among workers. The resulting average percent residual energies of individual workers are then set as constraints for the second model. Then, the second model is re-solved with an objective to minimize the total travel distance for all vehicles. The ILOG CPLEX is able to find the optimal solution of the first model (with the computation time of 4.6 s). For the second model, the ILOG CPLEX is unable to solve it to optimality. The program is terminated after 24 hours.

Table 5 shows percent residual energies of workers in each workday (from the second model). It is seen that for each worker, the physical workloads that one has to endure in the six workdays are not the same. For example, worker W6 has to work rather hard in workday D3 (percent residual energy = 22.8%) but work moderately in workday D4 (percent residual energy = 44.8%). The average percent residual energy during the delivery period of worker W6 is 33.6%, with a standard deviation of 9.6%. Among the ten workers, workers W2, W3, W5, W7, W9, and W10 have the maximum average percent residual energy of 44.7 %. Worker W8 has the minimum average percent residual energy of 30.9%.

Table 6 shows the delivery routes obtained from the second model. The best found total travel distance is 1,020 km. (Note that the total travel distance obtained from the first model is 1,174 km.) It is observed that large vehicles V1 and V2 are utilized more than small vehicles V3 and V4 since their average travel distances are longer. This is because they serve more customers in each workday.

Table 5 Percent residual energies (%) of workers (optimization approach)

Vehicle	Worker	Workday						Average	SD
		D1	D2	D3	D4	D5	D6		
V1	W1	32.8	38.0	32.8	26.8	32.8	38.4	33.6	4.3
	W2	44.0	48.3	44.0	39.0	44.0	48.7	**44.7**	3.5
	W3	44.0	48.3	44.0	39.0	44.0	48.7	**44.7**	3.5
V2	W4	29.6	36.0	22.8	44.8	24.4	44.0	33.6	9.6
	W5	41.3	46.7	35.7	54.0	37.0	53.3	**44.7**	8.0
	W6	29.6	36.0	22.8	44.8	24.4	44.0	33.6	9.6
V3	W7	40.0	40.0	42.4	49.0	55.6	41.2	**44.7**	6.3
	W8	25.0	25.0	28.0	36.3	44.5	26.5	30.9	7.9
V4	W9	52.6	40.0	46.0	42.4	41.2	46.0	**44.7**	4.6
	W10	52.6	40.0	46.0	42.4	41.2	46.0	**44.7**	4.6

Note: The bold face values are the maximum average percent residual energy.

Table 6 Delivery routes and travel distances (in parentheses) (optimization approach)

Day	Vehicle			
	V1	V2	V3	V4
D1	S→C6→C4→C1→C8→S (40 km)	S→C10→C9→S (38 km)	S→C5→C3→S (40 km)	S→C7→C2→S (32 km)
D2	S→C1→C5→C3→S (58 km)	S→C8→C10→C2→S (46 km)	S→C9→C7→S (36 km)	S→C6→C4→S (34 km)
D3	S→C3→C5→C4→S (56 km)	S→C6→C7→C9→S (54 km)	S→C8→C1→C10→S (40 km)	S→C2→S (30 km)
D4	S→C4→C6→C5→C3→S (56 km)	S→C7→C9→C2→S (36 km)	S→C1→S (22 km)	S→C8→C10→S (30 km)
D5	S→C1→C7→C9→S (58 km)	S→C5→C3→C10→S (40 km)	S→C6→C4→S (34 km)	S→C8→C2→S (40 km)
D6	S→C1→C10→C3→S (60 km)	S→C7→C9→C5→S (60 km)	S→C2→C6→S (48 km)	S→C8→C4→S (32 km)

4.1.2 Heuristic approach

The heuristic procedure is applied to determine percent residual energies of workers and delivery routes for vehicles in each workday during the delivery period. The procedure described in Section 4 is coded in a MATLAB m-file program. Firstly, the delivery routes are constructed (in Phase I). Secondly, the resulting maximum average fractional residual energy among workers is decreased (in Phase II). Also, the total travel distance is decreased using the 2-opt edge exchange.

Table 7 Percent residual energies (%) of workers (heuristic approach)

Vehicle	Worker	Workday						Average	SD
		D1	D2	D3	D4	D5	D6		
V1	W1	32.0	34.4	30.0	37.2	22.4	44.0	33.3	7.2
	W2	43.3	45.3	41.7	47.7	35.3	53.3	44.4	6.0
	W3	43.3	45.3	41.7	47.7	35.3	53.3	44.4	6.0
V2	W4	22.4	38.0	20.8	39.2	40.4	41.2	33.7	9.4
	W5	35.3	48.3	34.0	49.3	50.3	51.0	**44.7**	7.9
	W6	22.4	38.0	20.8	39.2	40.4	41.2	33.7	9.4
V3	W7	43.8	42.4	51.4	42.4	47.2	41.2	**44.7**	3.9
	W8	29.8	28.0	39.3	28.0	34.0	26.5	30.9	4.8
V4	W9	53.2	40.0	44.2	41.8	41.4	42.0	43.8	4.8
	W10	53.2	40.0	44.2	41.8	41.4	42.0	43.8	4.8

The results of the heuristic procedure are quite astounding. Table 7 shows percent residual energies of the 10 workers based on the heuristic procedure. The maximum and minimum average percent residual energies are 44.7% and 30.9%, respectively, which are equal to the maximum and minimum values obtained from the optimization approach (see Table 5).

Table 8 shows delivery routes and travel distances for all vehicles in each workday during the delivery period. The total travel distance is 1,138 km (which is 11.57% longer than the solution from the optimization approach). Remarkably, its total computation time is only 0.30 second.

Table 8 Delivery routes and travel distances (heuristic approach)

Day	Vehicle			
	V1	V2	V3	V4
D1	S→C3→C9→C2→S (60 km)	S→C10→C7→C4→S (56 km)	S→C6→C1→S (36 km)	S→C5→C8→S (44 km)
D2	S→C8→C1→C6→S (40 km)	S→C5→C4→C10→S (60 km)	S→C3→C2→S (56 km)	S→C9→C7→S (36 km)
D3	S→C6→C3→C8→S (54 km)	S→C2→C9→C10→C1→S (58 km)	S→C4→S (28 km)	S→C5→C7→S (50 km)
D4	S→C1→C6→C7→S (62 km)	S→C5→C3→C4→S (56 km)	S→C8→C10→S (30 km)	S→C9→C2→S (36 km)
D5	S→C9→C7→C3→S (60 km)	S→C1→C4→C6→C10→S (50 km)	S→C5→S (30 km)	S→C8→C2→S (40 km)
D6	S→C7→C9→C5→S (60 km)	S→C1→C4→C3→S (58 km)	S→C6→C2→S (48 km)	S→C8→C10→S (30 km)

4.2 Post-assignment policy

The assignment of worker-vehicle pairing in each workday is created after knowing the delivery route and carried load of vehicles. The first step is to find optimal delivery route of vehicle in each workday, secondly intend to assign workers to vehicle for minimizing maximum average percent residual energy among workers.

4.2.1 Optimization approach

In order to determine the result of delivery routes, the mathematical model is employed to solve with ILOG CPLEX separately on each workday. The result of delivery routes and total travel distance are optimal solution (total solving time 7.38 second with total travel distance 804 km). The delivery routes and travel distance are represented in table 9. Thus, the load quantity of each truck are known and shown in table 10.

Table 9 Delivery routes and travel distances (optimization approach-post assignment)

Day	Vehicle			
	V1	V2	V3	V4
D1	S→C5→C3→C6→S (40 km)	S→C8→C7→C10→S (38 km)	S→C9→C2→S (36 km)	S→C1→C4→S (30 km)
D2	S→C6→C5→C3→S (40 km)	S→C10→C2→C9→C7→S (38 km)	S→C1→C4→S (30 km)	S→C8→S (14 km)
D3	S→C7→C9→C2→S (36 km)	S→C5→C3→C6→S (40 km)	S→C8→C1→C10→S (40 km)	S→C4→S (28 km)
D4	S→C7→C9→C2→S (36 km)	S→C6→C5→C3→C10→S (40 km)	S→C4→C8→S (32 km)	S→C1→S (22 km)
D5	S→C5→C3→C6→S (40 km)	S→C2→C9→C7→S (36 km)	S→C10→C8→S (30 km)	S→C1→C4→S (30 km)
D6	S→C6→C4→C1→S (36 km)	S→C7→C9→C2→C10→S (38 km)	S→C8→S (14 km)	S→C5→C3→S (40 km)

Table 10 The carried load of each vehicle (units) (optimization approach)

Vehicle	Day					
	D1	D2	D3	D4	D5	D6
V1	163	174	179	138	192	159
V2	199	179	191	189	172	181
V3	97	81	96	90	89	51
V4	64	81	81	85	76	91

Table 11 Result of assignment (optimization approach)

Worker	Day					
	D1	D2	D3	D4	D5	D6
W1	V1	V2	V3	V1	V3	V4
W2	V2	V2	V2	V2	V3	V2
W3	V2	V1	V1	V2	V2	V1
W4	V4	V1	V3	V4	V1	V1
W5	V3	V1	V2	V2	V1	V2
W6	V2	V2	V2	V3	V4	V3
W7	V1	V3	V1	V3	V4	V2
W8	V4	V4	V4	V4	V2	V3
W9	V3	V4	V1	V1	V2	V4
W10	V1	V3	V4	V1	V1	V1

From the delivery routes in each workday, the loading quantity of each vehicle is known in advance. Based on the known carried loads, the result from CPLEX leads to the schedule of workers on each workday (total solving time 0.5 second). Table 11 shows result of workers-vehicles paring in each work. Table 12 shows percent residual energies of workers in each workday. The maximum average energy residual is 40.5% and minimum is 40.3% perfectly balance.

Table 12 Percent residual energies (%) of workers (optimization approach-post assignment)

Worker	Workday						Average	SD
	D1	D2	D3	D4	D5	D6		
W1	34.8	28.4	42.4	44.8	46.6	45.4	40.4	7.2
W2	33.7	40.3	36.3	37.0	55.5	39.7	40.4	7.8
W3	33.7	42.0	40.3	37.0	42.7	47.0	40.4	4.7
W4	61.6	30.4	42.4	49.0	23.2	36.4	**40.5**	13.7
W5	51.5	42.0	36.3	37.0	36.0	39.7	40.4	5.9
W6	20.4	28.4	23.6	46.0	54.4	69.4	40.4	19.5
W7	34.8	51.4	28.4	46.0	54.4	27.6	40.4	11.7
W8	52.0	39.3	39.3	36.3	14.0	61.8	40.4	16.2
W9	41.8	51.4	28.4	44.8	31.2	45.4	**40.5**	8.9
W10	34.8	51.4	51.4	44.8	23.2	36.4	40.3	11.0

4.2.2 Heuristic approach

The heuristic for determine delivery route in section 3.2 written in MATLA m-file yield a near optimal total travel distance equal 808 km (optimal 804 km) from phase II. The delivery route shows in table 13 and carried load of each vehicle shows in table 14. The computation time is 1.1 second.

Table 13 Delivery routes and travel distances (heuristic approach-post assignment)

Day	Vehicle			
	V1	V2	V3	V4
D1	S→C3→C10→S (40 km)	S→C2→C9→C7→C8→S (46 km)	S→C5→C6→S (30 km)	S→C1→C4→S (30 km)
D2	S→C2→C9→C7→C10→S (38 km)	S→C3→C5→C6→S (40 km)	S→C8→S (14 km)	S→C1→C4→S (30 km)
D3	S→C2→C9→C7→S (36 km)	S→C3→C5→C6→S (40 km)	S→C→C8→C10→S (42 km)	S→C4→S (28 km)
D4	S→C3→C5→C6→C4→S (56 km)	S→C2→C9→C7→C10→S (38 km)	S→C1→S (22 km)	S→C8→S (14 km)
D5	S→C2→C9→C7→S (36 km)	S→C3→C5→C6→S (40 km)	S→C1→C4→S (30 km)	S→C8→C10→S (30 km)
D6	S→C2→C9→C7→C10→S (38 km)	S→C1→C4→C6→S (36 km)	S→C8→S (14 km)	S→C3→C5→S (40 km)

Table 14 The carried load of each vehicle (units) (heuristic approach)

Vehicle	Day					
	D1	D2	D3	D4	D5	D6
V1	178	179	179	183	172	181
V2	191	174	191	164	192	159
V3	90	81	96	85	76	51
V4	64	81	81	70	89	91

After know the carried load of each vehicle, the heuristics for construct workers schedule in section 3.2.2 are employed to solve the problem. The solution of multi-workday assignment shows in table 15. The percent residual energy shows in table 16. The computation time is 0.17 second.

Table 15 Result of assignment (heuristic approach)

Worker	Day					
	D1	D2	D3	D4	D5	D6
W1	V4	V3	V2	V2	V1	V2
W2	V1	V2	V1	V1	V2	V1
W3	V1	V2	V1	V1	V2	V1
W4	V3	V3	V3	V2	V1	V2
W5	V3	V1	V2	V1	V2	V1
W6	V4	V4	V1	V2	V1	V2
W7	V2	V1	V3	V4	V4	V4
W8	V1	V4	V4	V4	V3	V3
W9	V2	V2	V4	V3	V4	V4
W10	V2	V1	V2	V3	V3	V3

Table 16 Percent residual energies (%) of workers (heuristic approach-post assignment)

worker	Energy residual on each day (%)						Mean	SD
	D1	D2	D3	D4	D5	D6		
W1	61.6	51.4	23.6	34.4	31.2	36.4	39.8	14.0
W2	40.7	42.0	40.3	39.0	36.0	39.7	39.6	2.0
W3	40.7	42.0	40.3	39.0	36.0	39.7	39.6	2.0
W4	46.0	51.4	42.4	34.4	31.2	36.4	40.3	7.7
W5	55.0	40.3	36.3	39.0	36.0	39.7	41.1	7.1
W6	61.6	51.4	28.4	34.4	31.2	36.4	40.6	13.0
W7	23.6	28.4	42.4	58.0	46.6	45.4	40.7	12.7
W8	11.0	39.3	39.3	47.5	43.0	61.8	40.3	16.6
W9	23.6	30.4	51.4	49.0	46.6	45.4	41.1	11.3
W10	23.6	28.4	23.6	49.0	54.4	69.4	**41.4**	19.0

5. Computation Experiment

Six MW-VRP problems (P1 to P6) are generated and tested. The smallest problem consists of 4 vehicles, 10 workers, and 10 customers, while the largest one consists of 8 vehicles, 18 workers, and 20 customers. Table 17 shows the numbers of customers, vehicles and workers used in each test problem. For each problem, both the optimization approach and heuristic approach are applied to obtain the MW-VRP solutions with two assignment policies (pre and post assignment). The results for pre and post assignment are presented in Table 18 and 19 respectively. For pre-assignment policy, it is noted that when formulating the problems as the first MW-VRP model, the ILOG CPLEX is able to solve them to optimality. However, none of the problems can be solved when they are formulated as the second MW-VRP model. The total distances shown in Table 18 are merely the best solutions obtained when the ILOG CPLEX is terminated after 24 hours of computation time.

Table 17 Six test problems for the MW-VRP computation experiment

Problem	Number of		
	Customers	Vehicles	Workers
P1	10	4	10
P2	10	4	10
P3	10	4	10
P4	15	6	14
P5	15	6	14
P6	20	8	18

Table 18 MW-VRP results of the 6 test problems pre-assignment policy

Problem	MW-VRP Solution (Optimization Approach)						MW-VRP Solution (Heuristic Approach)			
	First Model (Optimal)				Second Model					
	MAX	MIN	TD	CT	TD	CT	MAX	MIN	TD	CT
P1	44.1	30.1	1,716	921	1,218	86,400	44.2	30.2	1,586	0.59
P2	44.7	30.9	1,174	4.68	1,020	86,400	44.7	30.9	1,144	0.30
P3	43.8	29.8	1,122	12.42	918	86,400	45.1	31.4	1,120	0.07
P4	40.3	25.4	1,790	351.98	-	86,400	41.7	26.7	1,736	0.21
P5	40.0	25.0	1,676	191.16	-	86,400	42.6	24.3	1,576	0.15
P6	41.9	27.4	2,658	9,386.1	-	86,400	42.2	27.7	2,450	1.01

Note: MAX = maximum average percent residual energy (%); MIN = minimum average percent residual energy (%); TD = total travel distance (km); CT = computation time (s); - = unable to yield the feasible solution

Table 19 MW-VRP results of the 6 test problems post-assignment policy

Problem	MW-VRP Solution (Optimization Approach)					MW-VRP Solution (Heuristic Approach)				
	MAX	MIN	TD	TCR	TCA	MAX	MIN	TD	TCR	TCA
P1	37.7	37.5	1110	10.37	13.58	39.1	36.1	1150	1.28	0.17
P2	40.5	40.3	804	7.38	0.5	41.4	39.6	808	1.1	0.11
P3	39.6	39.2	782	5.92	1290.12	40.5	38.3	828	1	0.12
P4	35.4	35.1	1052	125.38	3125.5	35.7	34.7	1076	2.8	0.44
P5	33.7	33.3	1062	193.01	32.63	34.3	32.3	1102	2.6	0.28
P6	39.0	38.2	1472	1598.1	1990.99	39.2	38.5	1522	6.2	0.7

Note: TD=total travel distance; TCR and TCA = computation time (sec) for route and assignment respectively.

For pre-assignment policy, when comparing the maximum average percent residual energies, it is seen that the heuristic procedure is very effective in generating delivery routes such that the allocation of physical workloads among workers is close to the optimal result of each problem. The increase from the optimal result ranges from 0% to 6.5%. Regarding the total travel distance, we are unable to evaluate the effectiveness of the heuristic procedure since the minimum total travel distance (from the second MW-VRP model) cannot be obtained. However, by comparing the total travel distances obtained from the heuristic procedure to those obtained from the first MW-VRP model, the heuristic solutions are superior in all 6 test problems.

The heuristic procedure demonstrates outstanding performance with respect to computation time. Even for the largest test problem P6, it needs only 1.01 s to obtain the MW-VRP solution. For the same test problem, the ILOG CPLEX needs 9,386.1 s (about 2.60 h) to find the optimal solution for the first MW-VRP model.

For post-assignment policy as from experiment, the optimization program CPLEX can yield the optimal solution for all test problems. For the physical workload, the heuristic procedure yield a max average residual energy that deviate from optimal solution 0.51 to 3.58 percent and 0.5 to 5.56 percent for total travel distance. However, the computation time of heuristic procedure mostly less than one second that is very fast than optimization approach. The post-assignment policy is superior pre-assignment that can observe from gab between maximum and minimum average percent residual energies.

6. Conclusion

The multi-workday vehicle routing problem (MW-VRP) with ergonomic consideration of physical workload is discussed. During a given planning period which consists of several consecutive workdays, delivery routes of all vehicles throughout the period are determined such that all workers receive relatively equal physical workloads. Two policies of worker-vehicle assignment are evaluated. Firstly, workers are pre-assigned to vehicles at the beginning of the planning period. The worker-vehicle pairings are kept unchanged for every workday. Secondly, workers are post-assigned to vehicles. After the optimal delivery routes of all vehicles are separately determined for each workday, workers are then assigned to vehicles so as to balance their physical workloads over the planning period.

MW-VRP with the worker-vehicle pre-assignment policy is mathematically modeled and solved to determine the delivery routes of all vehicles so as to minimize the maximum average percent residual energy among all workers during the planning period. Different worker-vehicle assignment patterns also yield different solutions.

MW-VRP with the worker-vehicle post-assignment policy requires two problem-solving steps. Firstly, the optimal delivery routes of all vehicles are determined separately for each workday. Knowing the delivery routes, the required total energy expenditures to perform manual handling tasks in each workday can be determined. Secondly, all workers are assigned to the utilized vehicles such that the maximum average percent residual energy among the workers during the planning period is minimized. This 2-step approach yields not only the shortest total travel distance but also the well-balanced physical workload allocation during the planning period.

However, VRP and WSP are also considered as NP-hard problem. When problem size increasing, it is impossible to obtain an optimal solution in reasonable time. Thus, the heuristic procedure can yield us a near-optimal or an accepted solution in reasonable time. The heuristic procedures for both assignment policies are developed. The result represent that the heuristic procedure can yield an acceptance solution in very less time than optimization CPLEX.

Appendix B
Solution of Single-objective MW-EWSP model

Appendix B represents a detail of solution of single-objective MW-EWSP model both CPLEX and GA in Chapter 5: numerical example. The work schedule and daily hazard exposure are shown as following tables.

Table 1. Work schedule from OB1 CPLEX

Worker	D1				D2				D3			
	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4
M1	T5	-	T1	-	T4	T1	-	T1	T1	-	T4	-
M2	T2	T2	T2	T2	T2	T5	T5	-	T2	-	T5	T5
M3	T1	T1	T3	T3	T3	-	-	T3	T3	T1	T3	T3
M4	-	-	T4	-	-	T4	-	T2	T4	-	-	T4
M5	T4	-	-	-	-	-	T4	T4	-	T4	T2	T2
M6	T3	T3	T5	-	T5	-	T1	T5	T5	T5	T1	-
Worker	D4				D5							
	P1	P2	P3	P4	P1	P2	P3	P4				
M1	-	T5	T4	-	T4	-	T4	-				
M2	-	-	T5	T5	-	T5	T5	-				
M3	T4	-	T1	T1	T1	T4	T1	-				
M4	T5	T4	-	T2	T2	T1	-	T4				
M5	-	T1	T2	T4	T5	T2	T2	-				
M6	T1	-	T3	T3	T3	T3	T3	T5				

Table 2 Daily hazard exposures of the six workers from OB1 CPLEX

Worker	D1	D2	D3	D4	D5	Average	SD
M1	0.5822	0.9637	0.7030	0.7638	0.8846	0.7795	0.1500
M2	0.8876	0.8649	0.8649	0.6430	0.6430	0.7807	0.1260
M3	0.8626	0.3412	0.7725	0.9637	0.9637	0.7807	0.2583
M4	0.4423	0.6642	0.8846	0.9857	0.9249	0.7803	0.2246
M5	0.4423	0.8846	0.8861	0.9249	0.7653	0.7806	0.1984
M6	0.6627	0.9037	0.9037	0.6019	0.8333	0.7811	0.1405

Table 3 Work schedule from OB2 CPLEX

Worker	D1				D2				D3			
	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4
M1	T4	-	T4	-	T4	-	-	T4	T4	-	-	T4
M2	T5	-	T5	-	T5	T5	T5	-	T2	T5	T2	T2
M3	-	T3	T1	T3	T3	T1	T1	T1	T1	T1	T1	T3
M4	T2	T2	T2	T2	T2	-	T4	T2	-	T4	T4	-
M5	T1	T1	-	-	-	T4	-	T5	T5	-	T5	T5
M6	T3	-	T3	-	-	-	-	T3	T3	-	T3	-

Worker	D4				D5			
	P1	P2	P3	P4	P1	P2	P3	P4
M1	-	-	T4	T4	T4	-	-	T4
M2	T5	T5	T5	-	T2	T2	T2	T5
M3	T1	T4	-	T1	T1	T1	T1	-
M4	T4	-	T2	T2	-	T4	T4	-
M5	-	T1	T1	T5	T5	T5	T5	-
M6	-	-	T3	T3	T3	T3	T3	-

Table 4 Daily hazard exposures of the six workers from OB2 CPLEX

Worker	D1	D2	D3	D4	D5	Average	SD
M1	0.8846	0.8846	0.8846	0.8846	0.8846	0.8846	0.0000
M2	0.6430	0.9645	0.9872	0.9645	0.9872	0.9093	0.1493
M3	0.6019	0.9527	0.9527	0.9637	0.7821	0.8506	0.1583
M4	0.8876	0.8861	0.8846	0.8861	0.8846	0.8858	0.0013
M5	0.5214	0.7638	0.9645	0.8429	0.9645	0.8114	0.1832
M6	0.3412	0.1706	0.3412	0.3412	0.5118	0.3412	0.1206

Table 5 Work schedule from OB3 CPLEX

Worker	D1				D2				D3			
	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4
M1	T5	-	-	-	-	T4	-	T4	-	T4	-	T4
M2	T3	T3	T3	T3	T3	T5	-	T3	T3	-	T3	T3
M3	T1	T1	T1	-	-	T1	T1	T1	T1	T1	T1	-
M4	T2	T2	T2	T2	T2	-	-	T2	T2	T5	T2	T2
M5	T4	-	T4	-	T4	-	T4	-	T4	-	T4	-
M6	-	-	T5	-	T5	-	T5	T5	T5	-	T5	T5
Worker	D4				D5							
	P1	P2	P3	P4	P1	P2	P3	P4				
M1	T	T4	-	-	-	T4	-	T4				
M2	-	T5	T3	T3	T3	T3	-	T5				
M3	-	T1	T1	T1	T1	T1	T1	-				
M4	T5	-	T2	T2	T2	T2	T2	-				
M5	-	-	T4	T4	T4	-	T4	-				
M6	T1	-	T5	T5	T5	T5	T5	-				

Table 6 Daily hazard exposures of the six workers from OB3 CPLEX

Worker	D1	D2	D3	D4	D5	Average	SD
M1	0.3215	0.8846	0.8846	0.8846	0.8846	0.7720	0.2518
M2	0.6824	0.6627	0.5118	0.6627	0.8333	0.6706	0.1140
M3	0.7821	0.7821	0.7821	0.7821	0.7821	0.7821	0.0000
M4	0.8876	0.4438	0.9872	0.7653	0.6657	0.7499	0.2099
M5	0.8846	0.8846	0.8846	0.8846	0.8846	0.8846	0.0000
M6	0.3215	0.9645	0.9645	0.9037	0.9645	0.8237	0.2820

Table 7 Work schedule from OB1 GA

Worker	D1				D2				D3			
	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4
M1	T4	-	-	-	-	T4	-	T4	T3	T4	T3	-
M2	T2	-	T2	T3	T3	T5	-	T5	T2	-	T5	T5
M3	T3	T3	T3	-	T4	T1	-	T1	T1	-	T4	T3
M4	T5	-	T1	-	T2	-	T4	-	T4	T5	-	T2
M5	-	T2	T4	T2	-	-	T1	T2	-	T1	T2	T4
M6	T1	T1	T5	-	T5	-	T5	T3	T5	-	T1	-

Worker	D4				D5			
	P1	P2	P3	P4	P1	P2	P3	P4
M1	-	T4	T4	-	T4	T4	-	-
M2	-	T5	-	T5	T5	T5	T5	-
M3	T4	-	T3	T3	T1	T1	T1	-
M4	T5	-	T2	T2	-	T2	T2	T4
M5	T1	-	T1	T4	T2	-	T4	-
M6	-	T1	T5	T1	T3	T3	T3	T5

Table 8 Daily hazard exposures of the six workers from OB1 GA

Worker	D1	D2	D3	D4	D5	Average	SD
M1	0.4423	0.8846	0.7835	0.8846	0.8846	0.7759	0.1916
M2	0.6144	0.8136	0.8649	0.643	0.9645	0.7801	0.1488
M3	0.5118	0.9637	0.8736	0.7835	0.7821	0.7829	0.1691
M4	0.5822	0.6642	0.9857	0.7653	0.8861	0.7767	0.1630
M5	0.8861	0.4826	0.9249	0.9637	0.6642	0.7843	0.2048
M6	0.8429	0.8136	0.5822	0.8429	0.8333	0.7830	0.1129

Table 9 Work schedule from OB2 GA

Worker	D1				D2				D3			
	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4
M1	T4	-	T4	-	T4	-	-	T4	-	T4	T4	-
M2	T5	T2	T5	-	T5	T5	T5	-	T5	-	T5	T5
M3	T1	-	T3	-	-	T1	T4	T1	T1	T1	T1	-
M4	T2	-	T2	T2	T2	T4	-	T2	T2	-	T2	T4
M5	-	T1	T1	-	-	-	T1	T5	T4	T5	-	T2
M6	T3	T3	-	T3	T3	-	-	T3	T3	-	T3	T3
Worker	D4				D5							
	P1	P2	P3	P4	P1	P2	P3	P4				
M1	-	T4	-	T4	T4	T4	-	-				
M2	T5	-	T5	T5	T5	T2	T5	-				
M3	T4	-	T1	T1	T1	T1	T4	-				
M4	-	-	T4	T2	T2	-	T2	T4				
M5	T1	T1	T2	-	-	T5	T1	T5				
M6	-	T5	T3	T3	T3	T3	T3	-				

Table 10 Daily hazard exposures of the six workers from OB2 GA

Worker	D1	D2	D3	D4	D5	Average	SD
M1	0.8846	0.8846	0.8846	0.8846	0.8846	0.8846	0.0000
M2	0.8649	0.9645	0.9645	0.9645	0.8649	0.9247	0.0546
M3	0.4313	0.9637	0.7821	0.9637	0.9637	0.8209	0.2316
M4	0.6657	0.8861	0.8861	0.6642	0.8861	0.7976	0.1211
M5	0.5214	0.5822	0.9857	0.7433	0.9037	0.7473	0.1998
M6	0.5118	0.3412	0.5118	0.6627	0.5118	0.5079	0.1138

Table 11 Work schedule from OB3 GA

Worker	D1				D2				D3			
	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4
M1	T5	T1	T1	-	-	-	T4	T4	-	T4	-	T4
M2	T3	T3	T3	T3	T3	-	-	T3	T3	T5	T5	T3
M3	T1	-	-	-	-	T1	T1	T1	T1	-	T1	-
M4	T2	T2	T2	T2	T2	-	T5	T2	T2	-	T4	T2
M5	T4	-	T4	-	T4	T4	-	-	T4	T1	T2	-
M6	-	-	T5	-	T5	T5	-	T5	T5	-	T3	T5
Worker	D4				D5							
	P1	P2	P3	P4	P1	P2	P3	P4				
M1	-	T4	T4	-	T3	-	T5	T4				
M2	-	T5	T3	T3	T2	T3	T3	T5				
M3	T4	T1	-	T1	T1	T1	T1	-				
M4	-	-	T2	T2	T4	T2	T2	-				
M5	T1	-	T1	T4	-	T4	T4	-				
M6	T5	-	T5	T5	T5	T5	-	-				

Table 12 Daily hazard exposures of the six workers from OB3 GA

Worker	D1	D2	D3	D4	D5	Average	SD
M1	0.8429	0.8846	0.8846	0.8846	0.9344	0.8862	0.0324
M2	0.6824	0.3412	0.9842	0.6627	0.8846	0.7110	0.2473
M3	0.2607	0.7821	0.5214	0.9637	0.7821	0.6620	0.2742
M4	0.8876	0.7653	0.8861	0.4438	0.8861	0.7738	0.1918
M5	0.8846	0.8846	0.9249	0.9637	0.8846	0.9085	0.0355
M6	0.3215	0.9645	0.8136	0.9645	0.6430	0.7414	0.2696