Faculteit Bedrijfseconomische Wetenschappen

master handelsingenieur

Masterthesis

Personnel scheduling: studying the trade-off between personnel costs and employee preferences

Astrid Puttemans

Scriptie ingediend tot het behalen van de graad van master handelsingenieur, afstudeerrichting operationeel management en logistiek

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Personnel scheduling: studying the trade-off between personnel costs and employee preferences

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The literature on personnel scheduling has grown enormously over the past decades. Nowadays, employees have become increasingly demanding for the company to take their preferences into account. However, many personnel scheduling models incorporating those employee preferences are not implemented in practice. Determining the impact on the personnel costs at a time where employee preferences are increasingly being considered is not straightforward and only few research papers have made an effort to analyse the conflicting nature of personnel costs and employee preferences. Our purpose is to further investigate the trade-off relationship between personnel costs and employee preferences by means of trade-off curves. The analyses in this thesis are done based on a case study obtained from Knust and Schumacher (2011) in order to deduce results and insights.

Keywords: personnel scheduling, employee preferences, trade-off, mathematical programming

1. Introduction

Personnel scheduling is a research domain in which an extensive amount of literature has been published so far. Ernst et al. (2004, p. 3) defined personnel scheduling as ‘the process of constructing work timetables for its staff so that an organisation can satisfy the demand for its goods or services’. However, due to the fast-changing world, the increasing size and complexity of the problems and the significant economic benefits associated with good quality schedules, further research on personnel scheduling is still required (Valouxis, Gogos, Goulas, Alefragis, & Housos, 2012). Paycor, an organisation providing human resource management software, states that the personnel costs can account for up to 70% of the total business costs (Paycor, 2020). Therefore, the ability of an organisation to increase the quality of the personnel schedules can cut the personnel costs significantly.

Another reason that makes further research on personnel scheduling valuable, especially research on employee preferences, is that organisations are more and more explicitly integrating such preferences (e.g., requests for specific working days or shifts, assignments to a specific location or working partner and preferred durations or start times) into the schedule, as mentioned by Van den Bergh et al. (2013).

The major incentive for the incorporation of those preferences is to foster job satisfaction and, consequently, to reduce absenteeism and employee turnover (Stolletz & Brunner, 2012).

This paper focuses on combining those two facets of personnel scheduling, that is, minimising personnel costs and maximising employee preferences. However, a trade-off emerges because of the conflicting nature. This implies that progressing on both aspects simultaneously is extremely difficult, if not impossible. Furthermore, completely minimising the personnel costs or completely covering the preferences of the employees are usually not the desired outcomes in practice. Organisations are more likely to trade-off between costs and preferences to achieve a schedule that is favourable for them. The conflicting nature of personnel costs and employee preferences can be shown by means of trade-off curves, which give insights in the interactions and relationships between the two objectives. Most research papers, however, investigate a specific case and try to provide a single optimal solution, without studying the trade-off. Due to the highly constrained nature of personnel scheduling problems, finding such optimal solutions is hard. Yet, in practice, a set of solutions can be more valuable than just one solution. The increasing complexity in the world with many internal factors (e.g., resistance from the staff) as well as external factors (e.g., an economic recession, labour shortage or legislation and regulation) influencing personnel planning might imply that a different solution point from the set is a more effective choice in a given situation. For example, there can be resistance from the employees as soon as a certain level of preferences is not satisfied anymore. Through the solution set, it is then possible to determine the extent to which costs must be increased to meet a certain level of preference satisfaction. On the other hand, during a crisis, it is interesting for a company to see which point gives the lowest cost and whether this cost saving is sufficient to sacrifice on the employees' preferences. In general, there are many factors besides the personnel costs and the employee preferences themselves that can play a role in determining the most effective combination on both costs and preferences. A set of solutions allows for these additional factors to be implicitly considered.

Some papers on employee preferences have already slightly touched upon this trade-off aspect. Bard and Purnomo (2005), for example, ran their model several times with different maximum allowable penalties. Thereby, penalties were imposed for undesirable decisions in the adjusted schedule including the transfer of an employee to another unit, the transfer of an employee and subsequently assigning overtime during the next shift, the cancellation of an employee and an on-call assignment of an employee (Bard & Purnomo, 2005). As the maximum allowable penalties decreased, costs increased, and eventually it became infeasible to cover demand given the (low) number of penalties allowed (Bard & Purnomo, 2005). In Wright and Bretthauer (2010), the interaction between the schedule cost and the number of undesirable shifts was compared for two demand/supply coordination strategies (i.e., myopic and internal approach). The myopic coordination strategy implies that no float pool nurses (i.e., cross-trained nurses that do not have a home unit, but instead work in different units as needed) or agency nurses (i.e., nurses that are hired from a local agency on a temporary basis) are used to create the initial schedule (the planning phase). The only allowed option to match supply and demand is the use of overtime (Wright & Bretthauer, 2010). However, it is still allowed to use float pool nurses in the later allocation and adjustment phase of the schedule. In the internal approach, the use of float pool nurses is permitted to help remove overtime from the initial schedule (Wright & Bretthauer, 2010). Furthermore, these researchers already pointed out the nonlinearity in schedule costs in Wright, Bretthauer, and Côté (2006). More specifically, a slight increase in schedule cost can significantly improve the overall desirability of the schedule. However, the trade-off aspect in personnel scheduling was not the main conclusion of their research. A deeper focus on how such a trade-off curve is constructed and interpreted is therefore desirable. This research paper contributes to the literature and to managerial decision making by further investigating the trade-off relationship between personnel costs and employee preferences, using a case study provided by Knust and Schumacher (2011).

The remainder of the article is organised as follows: in Section 2, we begin by stating the problem and discussing the roles of the two involved parties (the employer and the employees). In Section 3, a literature overview is presented. We then offer the mathematical model for the personnel scheduling problem, along with the required data inputs and associated assumptions, in Section 4. The empirical results of the conducted analyses are highlighted in Section 5. Finally, we close with some main insights and recommendations for future research.

2. Problem statement

The focus of this paper is on a trade-off encountered during employee scheduling. Here, a balance must be made between the costs of the schedule and the preferences of employees.

Within the personnel scheduling domain, two interested parties are involved: the employer and the employees (Valouxis et al., 2012). Subsequently, two objectives can be distinguished. On the one hand, the employer is interested in lowering the personnel costs, considering legislation and employment contracts, as it is one of the highest cost components of a business. The employees, on the other hand, have preferences such as requests for specific shifts, specific working days and days off, preferred work durations as well as preferred start times or a preferred co-worker. Due to the present labour shortage and a greater consideration for the personal lives of employees, scheduling according to these preferences is crucial nowadays for the satisfaction and retention of the workforce. However, a high-quality schedule where minimum personnel costs are combined with maximum preference satisfaction is hard (if not impossible) to obtain.

To tackle this problem in practice, a trade-off curve gives the scheduler the opportunity to acquire insights in a set of optimal solutions balancing between the costs and the preferences, as shown in Figure 1. To obtain such curve, a bi-objective optimisation problem must be set up. In doing so, personnel costs are minimised while simultaneously the preferences are maximised, or in other words, penalty costs related to preference violations are minimised. Since doing equally well on both conflicting objectives is not possible, generating and considering only one optimal solution will not be the emphasis in this paper. The reason behind the conflicting nature of the personnel costs and preferences lies within the acquired flexibility for the scheduler. When taking more and more preferences into account, the flexibility the scheduler has for generating personnel schedules diminishes. Consequently, it will become harder to cover the demand with the available options. The scheduler will then be forced to switch to more expensive options or additional staffing to be able to cover all the demand.

The method that will be used for analysing the trade-off problem is the introduction of an additional constraint to the optimisation model, which controls the extent to which preferences can be violated. We then optimise the problem for different values of this constraint which will result in a curve quantifying the trade-off between both objectives.

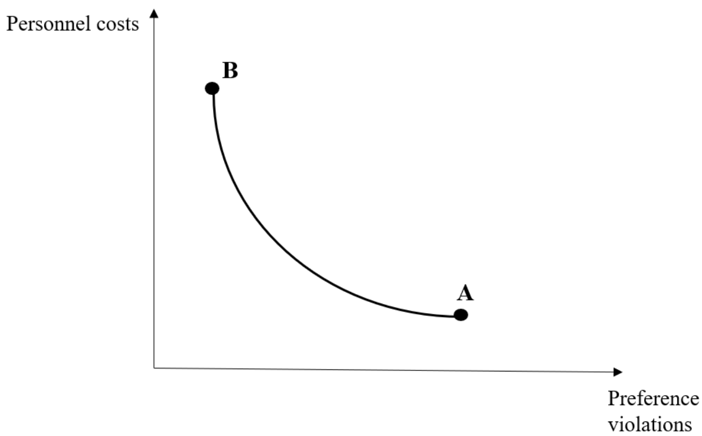

Figure 1 Concept of a trade-off curve

Figure 1 also depicts two extreme points. Either the personnel costs are very low, but the preferences are not well covered (A). Alternatively, the preferences are well covered, but the personnel costs are high (B). Between these two points, different combinations of the personnel costs for the schedule and the fulfilment of employee preferences are possible. It is up to the scheduler/employer to determine the final combination to be implemented.

3. Literature review

This section provides an overview of the relevant literature. In order to obtain a good understanding of the present personnel scheduling literature, the classification paper Van den Bergh et al. (2013) was used as the starting point.

There has already been a lot of research carried out on personnel scheduling. We focus our consultation of the literature on research papers that address employee preferences. Van den Bergh et al. (2013) already categorized the existing personnel scheduling literature according to several criteria including employee preferences. It is remarkable that only a few papers have done research on this subject, compared with other classification criteria. Moreover, Van den Bergh et al. (2013) mention that further research on coping with those preferences is needed. In addition, we place the focus of this paper on mathematical programming of a personnel scheduling problem. Combining the relevant papers of tables 11 and 13 of Van den Bergh et al. (2013) results in the following relevant literature papers, shown in Table 1.

Table 1 Overview of the literature on employee preferences, based on solution method

Integer programming	Mixed programming	Goal programming
Bard and Purnomo (2005); Pastor and Corominas (2010); Valouxis et al. (2012); Wright et al. (2006)	Cohn, Root, Esses, Kymissis, and Westmoreland (2006); Knust and Schumacher (2011); Sabar, Montreuil, and Frayret (2009); Sabar, Montreuil, and Frayret (2008); Stolletz and Brunner (2012); Wright and Bretthauer (2010)	Gordon and Erkut (2004); Topaloglu and Ozkarahan (2004)

3.1. Classification

This section provides a classification of the twelve relevant literature papers mentioned in Table 1, according to the 10 different dimensions shown in Table 2.

Table 2 Description of classification criteria

Dimension	Code	Descriptive dimension
Data	R	Real-world based data
	T	Theoretic data
Practice	Y	Actual implementation of solution in practice
	N	No actual implementation of solution in practice
Planning horizon	PH1	Less than or equal to 1 day (24 hours)
	PH2	More than 1 day but less than or equal to 1 week
	PH3	More than 1 week but less than or equal to 5 weeks
	PH4	More than 5 weeks
Inclusion of application	Y	With an application of the model
	N	Without an application of the model
Benchmarking	Y	Benchmarking applied
	N	No benchmarking applied
Context	H	Hospital
	AC	Assembly centres
	F-1	Facility
	F-2	Festival
	OC	Oil company
Methodology	M1	Mathematical optimisation
	M2	Two phase strategy/algorithm
	M3	Goal programming
	M4	Multi-agent-based approach
	M5	Heuristic procedure
Objective function	O1	Minimise costs of disruption between new and original plan/deviation from the target staffing requirements
	O2	Maximise overall suitability of the assignment configuration
	O3	Minimise total (operational) costs
	O4	Maximise multiple coverage
	O5	Minimise weighted sum of violations of the soft constraints
	O6	Minimise personnel dissatisfaction
	O7	Minimise paid out hours
	O8	Minimise range of assigned overtimes and/or undertimes
	O9	Minimise difference between min. and max. number of assigned on-call services
	O10	Minimise imbalance between number of shifts scheduled at the top and bottom gates/sum of deviations (= slack and surplus)
	O11	Maximise number of volunteer preferences
	O12	Minimise number of surplus volunteers
	O13	Maximise total training levels
	O14	Other objectives, e.g., minimise total understaffing, minimise the over-hours/under-hours assigned

Constraints	C1	Demand coverage requirements
	C2	Adequate rest provision
	C3	Flow constraints (floating/transfers)
	C4	Undesirable patterns
	C5	Overtime/Undertime
	C6	Maximum costs (optimal value)
	C7	Educational requirements
	C8	Number of vacation requests
	C9	Day-of-week preferences
	C10	Breaks
Decision variables	D1	Allocation of shifts
	D2	Allocation of units/gates
	D3	Allocation of overtime/undertime
	D4	Personnel flow
	D5	Staff surplus/shortage
	D6	Cancellation
	D7	Allocation of tasks/activities/trucks
	D8	Allocation of work pattern (work and rest days)
	D9	Allocation of breaks
	D10	Computation of deviations
	D11	Vacation requests
	D12	Day-of-week preferences

Table 3 discusses the first six dimensions of Table 2. These dimensions are aimed at giving a general view of some characteristics of the research papers. A first notable finding is that the majority of the papers address personnel scheduling in a hospital setting. This is probably due to the presence of a high labour shortage in healthcare. The ongoing COVID-19 crisis reaffirms the tremendous workload (both physically and mentally) and unattractive work schedules such as the night/weekend shifts nurses are facing. Therefore, including nurses' preferences could improve their dissatisfactions with the work schedules and, consequently, lower the current high turnover rate. In order to address the challenges caused by the nursing shortage, Wright and Bretthauer (2010) provide an overview of several internal and external coordination strategies that nursing managers have at their disposal for increasing personnel capacity. They investigate the use of agency nurses and the coordination with float pool nurses (i.e. nurses that do not have a home unit, but instead work in different units as needed) to expand service capacity and simultaneously reduce overtime (Wright & Bretthauer, 2010). Bard and Purnomo (2005), however, attempt to account for fluctuations by using overtime, on-call staff, agency, and float pool nurses. The main findings regarding the utilisation of coordination strategies are (1) that these strategies allow for an enormous reduction of the labour costs for the employer and (2) that they result in fewer undesirable shifts and less overtime for the employees (Wright & Bretthauer, 2010). Hence, the use of coordination strategies enhances the flexibility at which the scheduler can create work schedules for the employees. In addition, coordination can facilitate the incorporation of employee preferences such as requests for specific days or shifts. There is one important side note to be made on Bard and Purnomo (2005), however: the personnel gaps in their model were initially filled with the least expensive option, the use of pool nurses, while in reality the use of overtime is still the most preferred option in a hospital since it is the quickest and easiest option. The resulting costs must therefore be considered with a critical perspective.

Table 3 General characteristics describing the personnel scheduling models

Reference (Year)	Data	Practice	Planning horizon	Inclusion of application	Benchmarking	Context
Bard and Purnomo (2005)	R	N	PH1	Y	N	H
Pastor and Corominas (2010)	T	N	PH3	Y	Y	F-1
Valouxis et al. (2012)	R	N	PH3	Y	Y	H
Wright et al. (2006)	R	N	PH3	Y	Y	H
Cohn et al. (2006)	R	Y	PH4	Y	N	H
Knust and Schumacher (2011)	R	N	PH3	Y	Y	OL
Sabar et al. (2009)	T	N	PH1	Y	Y	AC
Sabar et al. (2008)	T	N	PH1	Y	N	AC
Stolletz and Brunner (2012)	R	N	PH3	Y	Y	H
Wright and Bretthauer (2010)	R	N	PH3	Y	Y	H
Gordon and Erkut (2004)	R	Y	PH2	Y	N	F-2
Topaloglu and Ozkarahan (2004)	R	N	PH2	Y	N	H

Furthermore, it can be seen from the "Planning horizon" column of Table 3 that a wide range of planning horizons is involved in personnel scheduling. One extreme example is Cohn et al. (2006), where a scope of one year is considered (since it concerned an academic year). To obtain a realistic schedule, the researchers invested heavily in the attributes of the model which are (1) easy to modify as changes occur over the year and (2) the model would have to be flexible as exceptions may exist to every implemented rule. In order to achieve these modelling goals, they undertook an entire process of trial-and-error by means of ongoing communication between the researchers and the application experts (Cohn et al., 2006). By doing so, attempts are made to clarify as much implicit information as possible and to represent this information properly in the model. Cohn et al. (2006) and Gordon and Erkut (2004) are the only papers in our literature overview that have applied the trial-and-error strategy. Note that these papers are also the only ones that were actually implemented, as shown in column “Practice” of Table 3. An increased use of the trial-and-error strategy might result in a more realistic model and thus improve the implementation rate.

Van den Bergh et al. (2013) also mentioned that a gap between theory and practice was at the origin of the low implementation rate of the developed personnel scheduling models. According to Van den Bergh et al. (2013), several issues are at play. Firstly, the personnel scheduling models are often not integrated with other scheduling problems (such as machine scheduling and operating room scheduling). In practice, however, these schedules do affect each other. Secondly, there is no personnel scheduling model that covers all aspects of personnel scheduling, which would include demand forecasting, adjusting the workload distribution, break placements, hiring/firing, considering employee preferences, training skills, machine scheduling and several other aspects. Typically, every developed model is missing at least one of these, which limits the applicability of the solution method in practice. Thirdly, Van den Bergh et al. (2013) note the low degree of uncertainty incorporation for reflecting real life events such as cancelled tasks, unavailable employees due to illness, arrival delays and so on. Finally, problems related to the software system can also hinder a proper implementation. It can be hard to implement the solution algorithm if the software is not available to the organisation, or if the organisation’s software does not allow to make suitable changes. Likewise, implementation can be hampered when the proposed algorithm is not clearly communicated and understood by the organisation’s IT specialists.

We then explored more deeply what may have caused the other literature papers of Table 3 to be unimplementable or which aspects are unrealistic in nature. Firstly, the use of theoretical data may have had an influence in this regard. Fortunately, the majority of the papers opted to work with real-world data, as can be seen in Table 3. Pastor and Corominas (2010) developed an extension on the model of Ulusam Seçkiner, Gökçen, and Kurt (2007) by adding suitability factors describing how suitable or preferable an employee is for performing a task given the hierarchical workforce setting. The researchers mentioned that these suitability factors depend on the motivation of the employee. However, it should be noted that the same suitability values were used for all employees in their approach. It can therefore be stated that homogeneity of the workforce was assumed. In reality, every employee is different. Considering heterogeneity will undoubtedly make the model more realistic for implementation in practice. In addition, Pastor and Corominas (2010) made additional assumptions that do not hold for all employees in practice: every employee works full-time, every employee can only work one shift type and each task requires only one employee. Wright et al. (2006), for example, already focused their model on assigning shifts to heterogeneous nurses. They included aspects such as different types of nurses, full-time/part-time, 8-hour or 12-hour shifts as well as whether or not a nurse wants to work on weekends.

Also noticeable are Sabar et al. (2008) and Sabar et al. (2009) in Table 4. Sabar et al. (2009) provide a different solution methodology for the model set up and solved in Sabar et al. (2008). The purpose of Sabar et al. (2009) was to tackle the complexity of their personnel scheduling problem. More specifically, it was pointed out in the results of Sabar et al. (2008) that the solution times will be enormous for larger size cases, such that the proposed mathematical model cannot be used reliably in an environment where fast results are required. Sabar et al. (2009) aim to address this problem with a multi-agent-based approach. In this approach, three algorithms are developed that use well-defined (priority) rules in order to (1) generate an initial solution, (2) create coalitions and (3) select certain coalitions with the aim of improving the initial solution.

The multi-agent approach assumes a system consisting of heterogeneous agents, which cooperate with each other to produce a personnel schedule. Thereby, four types of agents were defined (i.e., a production-agent, a station-agent, a coordination-agent and an employee-agent). An initial solution, resulting in each employee-agent possessing a set of activities, is formed by the coordination-agent taking into account the (priority) rules, the requirements of employees and their competences. Subsequently, coalitions are formed consisting of two employee-agents. These coalitions allow for negotiations to reach a potential mutual agreement on which activities/tasks to exchange in order to increase their individual profits, and in the end improve the global personnel scheduling solution (Sabar et al., 2009). The coordination-agent will select and implement one arbitrary, mutually agreed upon coalition from the list of possible coalitions. This process of forming and selecting coalitions is repeated until no better solution can be found. In general, the multi-agent-based approach is a rather iterative method for obtaining the best possible solution. Sabar et al. (2009) is the only paper that addresses the personnel scheduling problem through this approach. However, despite the good optimality results and the short computational times needed, a side note should be made. By applying the multi-agent system, assumptions have been made such as restricting a coalition to only two employees and assuming that they are perfectly aware of the corresponding pay-off of tasks. In reality, these assumptions are not always justified, and may therefore limit the practicability of this method. For further details on multi-agent systems, we refer to Wooldridge and Jennings (1995), Wooldridge (2009) and Balaji and Srinivasan (2010).

A final element that can be of an unrealistic nature is the use of weights in an objective function consisting of multiple components. Stolletz and Brunner (2012), for example, made use of this without justifying the weight of 1 for the cost component in the objective function and the weight of 0.001 for both fairness components in the objective function. To what extent the proportion between these two values is realistic can therefore not be confirmed. However, the researchers do indicate that the small weight assigned to the fairness aspects will neglect the influence of the fairness maximisation on cost minimisation. Furthermore, the researchers themselves proposed two approaches; a 1-step approach (using weights) and a 2-step approach (optimising the objective functions separately, and avoiding the use of weights). Yet, this 2-step approach only provides a suboptimal solution, by first minimising the cost objective and then maximising the fairness objective taking into account an additional constraint in which the obtained value of the costs is included. In conclusion, researchers should keep in mind that these elements have a significant impact on the quality of the proposed solutions when applied in practice.

Table 4 Further classification describing the personnel scheduling models

Reference (Year)	Methodology	Objective function	Constraints	Decision variables
Bard and Purnomo (2005)	M1	O1	C1, C2, C3, C4, C5	D1, D2, D3, D4, D5, D6
Pastor and Corominas (2010)	M1	O2	C1, C2, C6	D1, D7, D8
Valouxis et al. (2012)	M2	O3	C1, C2	D1, D8
Wright et al. (2006)	M2, M5	O3, O6	C1, C2, C4, C5, C9	D1, D3, D12
Cohn et al. (2006)	M1	O4	C1, C2, C3, C7, C8, C9	D1, D2, D4, D5, D11, D12
Knust and Schumacher (2011)	M2	O5	C1, C2, C4, C5	D1, D7
Sabar et al. (2009)	M4	O3, O6	C1, C2, C3, C4, C5, C10	D1, D3, D4, D7, D9, D10
Sabar et al. (2008)	M1	O3, O6	C1, C2, C3, C4, C5, C10	D1, D3, D4, D7, D9, D10
Stolletz and Brunner (2012)	M1, M2	O7, O8, O9	C1, C2, C4, C5	D1, D3, D8
Wright and Bretthauer (2010)	M2	O1, O3, O6, O11, O13	C1, C2, C3, C4, C5, C9	D1, D2, D3, D4, D5, D12
Gordon and Erkut (2004)	M1, M3	O10, O11, O12	C1, C2, C4	D1, D2, D5
Topaloglu and Ozkarahan (2004)	M1	O6, O10, O14	C1, C2, C4, C5, C9, C10	D1, D3, D5, D8, D9, D10, D12

Table 4 shows several criteria that allowed us to review and classify the models constructed in the relevant papers. Some elements of Table 4 have already been briefly mentioned above. However, there are some aspects related to preferences that we want to highlight in more detail. First of all, it is worth noting that every research paper incorporates some basic hard constraints into its model. That is, to ensure that there are sufficient demand coverage requirements (C1 in Table 2 & 4), and that adequate rest is provided for the employees (C2 in Table 2 & 4) expressed in terms of maximum one shift a day, a minimum amount of time between 2 consecutive shifts, a maximum number of consecutive working days etc. In addition, there are many soft constraints possible as listed in Table 2. Depending on the company, there may be some specific requirements with regard to the context of the company or self-imposed personnel policies. One personnel scheduling model that can develop appropriate personnel schedules for all contexts is very difficult, if not impossible, to obtain. It can therefore be stated that establishing general scheduling models is hard.

Another observation is related to the allocation of shifts and breaks. In each model, decision variables are incorporated concerning the allocation of shifts (D1 in Table 2 & 4) in order to meet the demand coverage. However, in practice, breaks throughout the shift duration are present. These breaks should be added to the model to provide a more realistic representation of the work schedule; neglecting them will cause the analyst to overestimate the amount of work that can be done during shift hours. Sabar et al. (2008), for example, defined three types of breaks; a morning break, a lunch break and an afternoon break and incorporated it in the shift duration of each employee. An entire matrix was developed by Topaloglu and Ozkarahan (2004) whereby 1h-breaks were included in the different types of shifts. In a different model, the inclusion of breaks was not directly included in the constraints, but a prior algorithm was created resulting in a matrix of 140 daily shift types with breaks (Stolletz & Brunner, 2012). The other 9 research papers did not incorporate breaks.

Also, employees have their preferences regarding vacation time. In Knust and Schumacher (2011), each employee was allowed to specify the days he did not want to work (vacation days). However, when solving the model, the vacations were randomly distributed to the employees. Furthermore, when the employee could not reach his minimal working time since he requested too much vacation, the corresponding working time was reduced (Knust & Schumacher, 2011). This is probably because the model proceeds in a way where the hard constraints must be satisfied and additionally, the soft constraints must be fulfilled as much as possible. The total working time of an employee is covered by a soft constraint and could therefore be adjusted to the desired total working time interval of the employee. We believe, instead, that in practice it is more common to reduce the number of vacation days rather than the working time. Consequently, the applicability of the results must be considered with some caution. Moreover, the results also showed that the company does not have sufficient employees to satisfy the demand without any vacation requested. One of the recommendations included increasing the maximal working times (Knust & Schumacher, 2011). It must be noted that the work contracts of the employees as well as the driving and resting times of the workers must still be considered when increasing these working times. Besides the previously reviewed paper, Cohn et al. (2006) have also added vacation requests into their model.

Some models described their objective function as maximising the employee preferences. However, maximising the preferences will not lead to the fulfilment of every employee’s preferences in all cases.

For example, it is possible that for one employee all his preferences have been respected while for another employee only one or even no preferences have been respected. The inclusion of fairness aspects could overcome this. Cohn et al. (2006) did this by adding constraints to ensure a lower bound on the quality of each person's solution. Stolletz and Brunner (2012), on the other hand, incorporated three fairness aspects which are (1) stable shift starting times within each week, (2) an even distribution of working hours and (3) an even assignment of on-call services. The other papers did not include fairness into their models. This was for example visible in the obtained results of Sabar et al. (2008), which showed a huge discrepancy between the employees in terms of the number of working hours and the number of different activities that needed to be done. Fairness aspects could improve these results.

The last topic related to preferences is the modelling of flexibility in the personnel scheduling problems. Several research papers have tried to add flexibility elements to their model. The perceived advantage seen by the researchers is an increased flexibility for the scheduler/manager in developing schedules that cover the real-time varying demand. For instance, Topaloglu and Ozkarahan (2004) included start-time flexibility, shift-length flexibility, break-placement flexibility and days-off flexibility, start-time float (i.e., different start times allowed across the assigned work days of the week) and shift-length float (i.e., different lengths allowed on different days of the week). Some other papers included only a few of these elements. In particular, Sabar et al. (2008) only included shift start-time flexibility and break-placement flexibility. On the other hand, Stolletz and Brunner (2012) and Gordon and Erkut (2004) focus on shift start-time flexibility and shift-length flexibility. Gordon and Erkut (2004) cited that allowing different sets of shifts, that is, a combination of a 4-hour shift and a 2-hour shift or two 3-hour shifts allowed them to both meet the requirement of six hours per day and be able to develop a smoother shift set that met all demand. Stolletz and Brunner (2012) found, however, that a reduction of the maximum shift length leads to higher costs due to less flexibility. Apart from the advantage for the scheduler/manager, flexibility can also be seen as a benefit for the employees, as they now have multiple choices at their disposal (e.g., choosing their starting time or having a certain time window during which they can take a break). However, Stolletz and Brunner (2012) state (based on discussions with employees) that tighter starting time windows promote employee job satisfaction. While they present the preferability of tight start time windows as a managerial insight, the results show that the costs resulting from such windows can actually increase; consequently, the value of this insight is questionable. Wright and Bretthauer (2010) state that flexibility can be achieved by cross-training of employees. They find that increasing the level of cross-training leads to improvements in the objective function, but with diminishing returns. In addition, cross-training of float nurses proves to be more beneficial than transferring unit nurses from their home unit to another unit.

In general, each research paper inserts its own elements to address the preferences of employees in the personnel scheduling problem. The results so far have already been very promising. Wright et al. (2006), for example, stated that the number of undesirable shifts can be reduced substantially without extra costs. Stolletz and Brunner (2012), on the other hand, confirmed that overtime is a very costly option, especially for service organisations such as hospitals. Accordingly, the researchers formulated their objective function as a minimisation of the paid-out hours.

However, the implementation rate of all these results remains extremely low. This might indicate a lack of insight into the interplay that exists between the employees' preferences and the personnel costs. Therefore, by means of a trade-off curve we aim at providing a better understanding of the research question: 'If we allow the preferences of the employees to be violated to a certain level, what do we get in return in terms of cost savings?'.

4. Methodology

In this section, the context for the empirical study is presented, as well as the data inputs and structure of the personnel scheduling model along with the associated assumptions.

To investigate the trade-off between personnel costs and employee preferences, a personnel scheduling model must first be constructed. In order to do so, we relied to a great extent on the studied problem of scheduling tank trucks investigated by Knust and Schumacher (2011). The main reason why this paper has been chosen out of the relevant literature papers is the presence of a comprehensive description of the real-world data inputs, obtained from the oil company under investigation. This data has been used and eventually adjusted in the further analysis (see Section 4.3 Data inputs) and has been taken from Knust and Schumacher (2011) itself and from the webpage provided (http://www2.informatik.uni-osnabrueck.de/kombopt/data/tanktrucks/).

The researchers developed a mixed integer linear programming formulation with the objective of satisfying eight hard constraints, while fulfilling as much as possible of four soft constraints. Our research starts from this MIP formulation. However, our analysis will take into account the eight hard constraints given in Table 5, but only two of the four soft constraints shown in Table 6. Regarding the two other soft constraints that we leave out of consideration, Knust and Schumacher (2011) mentioned that these constraints were found to be the least important for the small oil company. These constraints would ensure that (1) the drivers are not assigned to a large number of different trucks in a week and (2) that the drivers do not often change the assigned trucks in a week.

Table 5 Hard constraints (based on Knust and Schumacher (2011))

H1	A suitable driver is assigned to every shift on all days;
H2	Each driver is assigned to at most one shift per day;
H3	Each driver is only assigned to a shift if he is accessible on that day;
H4	Each driver drives at most 55 hours per week;
H5	No driver has an early shift on the day directly after a late shift;
H6	No driver has both early and late shifts in a week;
H7	Each driver from the set N^{cw} does not have the same type of shifts (early or late) in two consecutive weeks;
H8	All permanent drivers: • Do not work only one day per week; • If they have free days in a week (which are not explicitly specified as vacation days), these days must be enlargements of the weekend;

Table 6 Soft constraints (based on Knust and Schumacher (2011))

S1	Every driver has an actual working time within his desired total working time interval;
S2	The trucks are assigned to more preferred drivers;

4.1. Context

The small oil company that participated in Knust and Schumacher (2011) consists of a set of drivers $N = \{1, \ldots, n\}$, which can be divided into a group of permanent drivers N^p and a group of temporary drivers N^t. A personnel schedule is produced for a time span of one month $\mathcal{T}$ (from Monday to Saturday), assuming $W = \{1, \ldots, w\}$ the number of weeks in $\mathcal{T}$. In this, the assumption was made that five weeks are involved within this time span $\mathcal{T}$. Furthermore, $\mathcal{T}^{Mo}$, $\mathcal{T}^{Tu}$, $\mathcal{T}^{We}$, $\mathcal{T}^{Th}$, $\mathcal{T}^{Fr}$ and $\mathcal{T}^{Sa} \subset \mathcal{T}$ can be derived as the sets of Mondays, Tuesdays, Wednesdays, Thursdays, Fridays and Saturdays in the time span $\mathcal{T}$. Similarly, $\mathcal{T}_1, \mathcal{T}_2, \mathcal{T}_3, \mathcal{T}_4$ and $\mathcal{T}_5 \subset \mathcal{T}$ can be created that represent the set of all days in week $w \in W$.

Besides, there is a set V that represents the number of tank trucks owned by the oil company (Knust & Schumacher, 2011). These trucks have to operate in early and/or late shifts depending on the day, which are given in the set S(t) where every shift is defined as a combination of a tank truck $v \in V$ and a shift type $p \in P$. This set, S(t) which includes all shifts that need to be covered, can also be split into a set $S^1(t)$ containing all early shifts and a set $S^2(t)$ containing all late shifts. In this study, the assumption made is that the first three tank trucks drive both an early and a late shift, while the remaining tank trucks only drive an early shift from Monday to Friday. For Saturday, an underlying assumption was made that only the first four trucks drive a shift on that day, more specifically an early shift. Regarding the shifts, the set $N_{(v,p)}$ consists of the drivers that are allowed for each particular shift and a set N^{cw} specifies the drivers who, for private reasons, are unable to work the same shift type in two consecutive weeks. In addition, a shift length l_t is defined depending on the day $t \in \mathcal{T}$.

Concerning the allocation of a driver to a tank truck, the use of suitability coefficients $\alpha_{jv} \in [0,1]$ is applied. A list was drawn up by the researchers in Knust and Schumacher (2011) after some computational tests and discussions with the oil company. This list, which ranks the suitable drivers for each truck from most suitable to least suitable, was also used in this study. However, a side note should be made about those ranking coefficients. A coefficient of $\alpha_{jv} = 0$ is set for the most suitable driver, $\alpha_{jv} = 1$ for the non-qualifying drivers and a gradation of coefficients $\alpha_{jv} \in]0,1[$ is used for suitable drivers whereby more suitable drivers get a smaller coefficient. Nevertheless, the explicit reasoning behind this ranking was not provided. To what extent this ranking (coefficients) is realistic is therefore hard to derive from the information given in Knust and Schumacher (2011).

Moreover, it was also mentioned that the oil company specifies an interval for each driver $j \in N$ with Z_j^{min} being the minimum desired total working time and Z_j^{max} the maximum desired total working time for that driver (Knust & Schumacher, 2011). The extent to which it is realistic to use such an interval is questionable. Therefore, it is our preference to use a different, more realistic approach in our study. First of all, the permanent drivers have a fixed contract in which a fixed number of working hours is specified and hence a fixed salary is granted. As a result, it is more reasonable to set Z_j^{min} and Z_j^{max} at the same value for the permanent drivers. If permanent drivers work less hours than stipulated in their contract, they are still paid for the stipulated number of working hours. If permanent drivers work overtime, that is, more hours than stipulated, they are paid an additional fee for each overtime hour worked. Additionally, in the model, it is decided to treat the temporary drivers as temporary hired workers, such that the working time interval values used in the model of Knust and Schumacher (2011) were applied. The Z_j^{min} values being 0 indicate that the temporary drivers will only be used when insufficient permanent drivers are available. For the Z_j^{max} values, a smaller cap was put on the maximal working time that can be asked from the hired workers than from the permanent drivers. Here, it is assumed that the oil company has agreed a contract with a subcontractor for Z_j^{max} working hours for each temporary driver. The personnel costs for these Z_j^{max} hours are therefore part of the agreed contract. As an employer today is strongly confronted with a limited labour market, it was decided to retain this point of view on the working time interval for temporary drivers. As a result, in general Z_j^{max} ($\forall N^p$) will be greater than Z_j^{max} ($\forall N^t$). Moreover, the performed hours above the limit Z_j^{max} are considered in further analyses as the overtime hours of the temporary drivers, for which an additional cost per hour still has to be paid.

In addition, there was the possibility for each driver to define a number of days where he does not want to work (vacation), represented by U_{jt}. Knust and Schumacher (2011) developed up to 15 different situations in which vacation days are granted. In the first case, vacation days are only granted to two temporary drivers as these two drivers are only available on Saturdays. Consequently, all the other days (Monday to Friday) are considered as vacation days. In the other 14 situations, additional vacation days are distributed randomly among the drivers (Knust & Schumacher, 2011). In this study, the first situation is followed for the simple reason that the results in Knust and Schumacher (2011) showed that, even without any additional vacation, overtime was already unavoidable. Moreover, randomly granting vacation days is not realistic, as discussed earlier in the literature review.

A dummy driver is introduced into the MIP model to ensure a feasible, complete personnel schedule. This dummy driver is assumed to be a qualified driver for all tank trucks, and is allowed to drive more than one tank truck on the same day. However, since it is not desirable that this dummy driver is assigned in the personnel schedule, high penalty costs are charged when Z_j^{min} = Z_j^{max} = 0 is violated.

Last, several weights are used that function as penalty cost factors in case of deviations from the soft constraints (S1) and (S2). In Knust and Schumacher (2011), a deviation from the desired total working time (S1) is penalised with w_j^+ for working times larger than Z_j^{max} and with w_j^- for working times smaller than Z_j^{min}. In this research, however, a different approach is followed. First of all, no penalty cost is charged when the working times are smaller than Z_j^{min}, since it was pointed out earlier that for the permanent drivers the company pays for a predefined number of hours anyway. For the temporary drivers, it is infeasible to attribute an undertime penalty cost factor since it is not possible to work less than Z_j^{min} = 0. The penalty cost factor w_j^- is therefore irrelevant and is set to 0. The cost factor w_j^+, however, is relevant and will assign an extra cost in case the working hours are greater than Z_j^{max}. For the permanent drivers, w_j^+ represents an extra cost for the company for each overtime hour worked on top of the base salary. For the temporary drivers, it also reflects an extra cost for each hour worked on top of the limited Z_j^{max} contractually agreed upon. The weight w_j^+ is given different values depending on the type of driver (permanent, temporary or dummy) and following the reasoning that in practice, assigning overtime to a permanent employee does not make it more expensive than hiring a temporary worker. Therefore, the largest weight is for the dummy driver, followed by the temporary drivers and with the smallest weights for the permanent drivers. The cost factor $\widehat{w_j}$ on the other hand will penalise situations where a driver is assigned to a tank truck for which he is not the most favoured driver (S2). The approach of Knust and Schumacher (2011) is followed, with smaller penalty weights for temporary drivers as they are generally not seen as one of the more preferred drivers.

4.2. Model formulation

In this section, a mixed integer linear programming model for the described scheduling problem is given, including all hard constraints (H1) – (H8) and soft constraints (S1) – (S2).

4.2.1. Notation

The following notation is used to develop the mixed integer programming formulation given in Section 4.2.2.

Sets

$W = \{1, \dots, w\}$	Set of weeks in planning horizon $\mathcal{T}$
$\mathcal{T} = \{1, \dots, \mathcal{T}\}$	Set of time periods (days) in the planning horizon
$\mathcal{T}^{Mo} \subset \mathcal{T}$	Set of all Mondays
$\mathcal{T}^{Tu} \subset \mathcal{T}$	Set of all Tuesdays
$\mathcal{T}^{We} \subset \mathcal{T}$	Set of all Wednesdays
$\mathcal{T}^{Th} \subset \mathcal{T}$	Set of all Thursdays
$\mathcal{T}^{Fr} \subset \mathcal{T}$	Set of all Fridays
$\mathcal{T}^{Sa} \subset \mathcal{T}$	Set of all Saturdays
$\mathcal{T}^{MoFr} \subset \mathcal{T}$	Set of all days from Monday to Friday
$\mathcal{T}_1 \subset \mathcal{T}$	Set of all days in week 1
$\mathcal{T}_2 \subset \mathcal{T}$	Set of all days in week 2
$\mathcal{T}_3 \subset \mathcal{T}$	Set of all days in week 3
$\mathcal{T}_4 \subset \mathcal{T}$	Set of all days in week 4
$\mathcal{T}_5 \subset \mathcal{T}$	Set of all days in week 5
V	Set of tank trucks
$N = \{1, \dots, n\}$	Set of drivers
$N^p \subset N$	Set of permanent drivers
$N^t \subset N$	Set of temporary drivers
$N^{cw} \subset N$	Set of drivers which should not have the same type of shift in two consecutive weeks
d	Dummy driver
$N^a = N \cup d$	Set of drivers and dummy driver
P	Set of shift types in the planning horizon
S(t)	Set of all shifts (combination of tank truck and shift type) on day t $\in \mathcal{T}$
$S^1(t) \subset S(t)$	Set of early shifts on day t $\in \mathcal{T}$
$S^2(t) \subset S(t)$	Set of early shifts on day t $\in \mathcal{T}$
$N_{(v,p)} \subset N$	Set of all drivers which may be assigned to shift (v,p)
$N^d_{(v,p)} \subset N^a$	Set of all drivers and dummy driver which may be assigned to shift (v,p)

Indices

t or t'	Index for time periods (days) in planning horizon
j	Index for drivers
v	Index for trucks
p	Index for shift types
w	Index for weeks

Parameters

h_1	Number of weeks in $\mathcal{T}$
h_2	Number of drivers
h_3	Number of trucks
l_t	Length of shifts on day $t \in \mathcal{T}$
U_{jt}	Parameter equal to 1 when day $t \in \mathcal{T}$ for driver $j \in N$ is a vacation day; 0 otherwise
Z_j^{min}	Desired minimal working time for driver $j \in N$
Z_j^{max}	Desired maximal working time for driver $j \in N$
w_j^+	Penalty cost factor for an overtime deviation from the desired total working times for driver $j \in N^a$
w_j^-	Penalty cost factor for an undertime deviation from the desired total working times for driver $j \in N^a$
$\widehat{w_j}$	Penalty cost factor for driver $j \in N$ when he is not the most favoured driver for the assigned truck
$\alpha_{jv} \in [0,1]$	Suitability coefficient of driver $j \in N$ for tank truck $v \in V$
X	Number of overtime hours that may be requested from $j \in N^p$

Decision variables

x_{jtvp}	1 if shift (v,p) is assigned to driver j on day t; 0 otherwise
D_j^+	Measures the overtime deviations for the drivers from their desired total working times
D_j^-	Measures the undertime deviations for the drivers from their desired total working times
v_{jw}^1	1 if driver j is assigned to early shifts in week $w \in W$; 0 otherwise
v_{jw}^2	1 if driver j is assigned to late shifts in week $w \in W$; 0 otherwise

4.2.2. Formulation

Using this notation, the personnel scheduling problem can be formulated as follows.

$$min \sum_{j \in N^a} (w_j^+ D_j^+ + w_j^- D_j^-) + \sum_{t \in \mathcal{T}} \sum_{(v,p) \in S_t} \sum_{j \in N_{(v,p)}} \widehat{w_j}\, \alpha_{vj} x_{jtvp} \tag{1}$$

$$\sum_{j \in N^d_{(v,p)}} x_{jtvp} = 1 \qquad (t \in \mathcal{T}, (v,p) \in S_t) \tag{2}$$

$$\sum_{(v,p) \in S_t} x_{jtvp} \leq 1 \qquad (j \in N, t \in \mathcal{T}) \tag{3}$$

$$\sum_{(v,p) \in S_t} x_{jtvp} = 0 \qquad \left(j \in N, t \in \mathcal{T} \cap U_{jt}\right) \tag{4}$$

$$\sum_{t \in \mathcal{T}_W} \sum_{(v,p) \in S_t} l_t x_{jtvp} \leq 55 \qquad (j \in N, \forall W) \tag{5}$$

$$\sum_{(v,p) \in S^2_t} x_{jtvp} + \sum_{(v,p) \in S^1_{t+1}} x_{j,t+1,vp} \leq 1 \qquad (j \in N, t \in \mathcal{T}^{MoFr}) \tag{6}$$

$$\sum_{(v,p) \in S^1_t} x_{jtvp} + \sum_{(v,p) \in S^1_{t'}} x_{jt'vp} \leq 1 \qquad (j \in N^{cw}, t \in \mathcal{T}_w, t' \in \mathcal{T}_{w+1}, \forall W) \tag{7}$$

$$\sum_{(v,p) \in S^2_t} x_{jtvp} + \sum_{(v,p) \in S^2_{t'}} x_{jt'vp} \leq 1 \qquad (j \in N^{cw}, t \in \mathcal{T}_w, t' \in \mathcal{T}_{w+1}, \forall W) \tag{8}$$

$$\sum_{t \in \mathcal{T}} \sum_{(v,p) \in S_t} l_t x_{jtvp} - Z^{max}_j - D^+_j \leq 0 \qquad (j \in N^a) \tag{9}$$

$$Z^{min}_j - \sum_{t \in \mathcal{T}} \sum_{(v,p) \in S_t} l_t x_{jtvp} - D^-_j \leq 0 \qquad (j \in N^a) \tag{10}$$

$$\sum_{t \in \mathcal{T}_W} \sum_{(v,p) \in S^1_t} x_{jtvp} - |\mathcal{T}_w| v^1_{jw} \leq 0 \qquad (j \in N, \forall W) \tag{11}$$

$$\sum_{t \in \mathcal{T}_W} \sum_{(v,p) \in S^2_t} x_{jtvp} - |\mathcal{T}_w| v^2_{jw} \leq 0 \qquad (j \in N, \forall W) \tag{12}$$

$$v^1_{jw} + v^2_{jw} \leq 1 \qquad (j \in N, \forall W) \tag{13}$$

$$\sum_{t \in \mathcal{T}_W} \sum_{(v,p) \in S_t} x_{jtvp} - 2(v^1_{jw} + v^2_{jw}) \geq 0 \qquad (j \in N^p, \forall W) \tag{14}$$

$$\sum_{(v,p) \in S_{t-1}} x_{j,t-1,vp} - \sum_{(v,p) \in S_t} x_{jtvp} \leq 0 \qquad \left(j \in N^p, t \in \mathcal{T}^{Tu} \setminus U_{jt}\right) \tag{15}$$

$$\sum_{(v,p) \in S_{t-2}} x_{j,t-2,vp} + \sum_{(v,p) \in S_{t-1}} x_{j,t-1,vp} - 2 \sum_{(v,p) \in S_t} x_{jtvp} \leq 0 \quad \left(j \in N^p, t \in \mathcal{T}^{We} \setminus U_{jt}\right) \tag{16}$$

$$\sum_{(v,p) \in S_{t+1}} x_{j,t+1,\mathrm{vp}} + \sum_{(v,p) \in S_{t+2}} x_{j,t+2,vp} - 2 \sum_{(v,p) \in S_t} x_{jtvp} \leq 0 \quad \left(j \in N^p, t \in \mathcal{T}^{Th} \setminus U_{jt}\right) \tag{17}$$

$$\sum_{(v,p) \in S_{t+1}} x_{j,t+1,\mathrm{vp}} - \sum_{(v,p) \in S_t} x_{jtvp} \leq 0 \qquad \left(j \in N^p, t \in \mathcal{T}^{Fr} \setminus U_{jt}\right) \tag{18}$$

$$x_{jtvp} = 0 \qquad \left(t \in \mathcal{T}, (v,p) \in S_t, j \in N \setminus N_{(v,p)}\right) \tag{19}$$

$$x_{jtvp} \in \{0,1\} \qquad (j \in N^a, t \in \mathcal{T}, (v,p) \in S_t) \tag{20}$$

$$v^1_{jw}, v^2_{jw} \in \{0,1\} \qquad (j \in N, \forall W) \tag{21}$$

$$D_j^+, D_j^- \geq 0 \qquad (j \in N^a) \tag{22}$$

$$D_j^+ \leq X \qquad (j \in N^p) \tag{23}$$

The objective function (1) adds the penalty costs for each violation of the soft constraints (S1) and (S2) from Table 6. The first term is associated with the deviations around the total desired working time interval of the drivers. Both positive (overtime) and negative (undertime) deviations are multiplied with a penalty cost factor and summed up over the drivers. The second term in (1) accounts for violations related to less preferred drivers assigned to the tank trucks. It follows that the aim is to minimise these violation costs and thus minimise objective function (1). Constraint (2) ensures that all shifts $(v, p) \in S_t$ in the time span are covered. This means that for each truck associated with a shift type (early/late), a driver is always assigned. By doing so, hard constraint 1 from Table 5 is fulfilled. Hard constraint 2 is addressed by constraint (3) in the presented model. It ensures that each driver is provided with adequate rest by restricting each driver to a maximum of one shift per day. Constraint (4) ensures that the drivers' vacation days are taken into account when assigning shifts to them (hard constraint 3). Constraint (5) guarantees that a driver does not drive more than 55 hours per week, also reflected in hard constraint 4 from Table 5. Constraint (6) copes with hard constraint 5 whereby no driver has an early shift on the day directly after a late shift. Hence, this constraint also ensures enough rest provisions for the drivers. Hard constraint 7 is handled by both constraints (7) and (8) which ensure that the drivers from subset N^{cw} do not have the same shift type in two consecutive weeks. Constraints (9) and (10) make sure that the decision variables D_j^+ and D_j^- for each driver are equal to the deviations of the driver's total desired working time $[Z_j^{min}, Z_j^{max}]$. In addition, constraints (11) and (12) enforce that binary variables v_{jw}^1 and v_{jw}^2 are set equal to 1 in case a driver is assigned to an early or a late shift in week w, respectively. The hard constraint 6 of Table 5 is respected by constraint (13) in the model. Thereby, it is imposed that no driver has both early and late shifts in a week. Constraint (14) enforces that all permanent drivers do not work only one day per week but rather work at least two days in a week or no day at all (part 1 of hard constraint 8). The following four constraints (15) – (18) deal with the obligation that if permanent drivers have days off in a week, which are not explicitly specified as vacation days, then these days are extensions of the weekend (part 2 of hard constraint 8). By way of explanation, constraint (15) ensures that if a driver has a free Tuesday, he is not allowed to work on the preceding Monday. Similarly, constraint (16) imposes that if a driver has a free Wednesday, he is not allowed to work on the preceding Monday and Tuesday. Constraint (17) implies that a driver is not permitted to work on the following Friday and Saturday if he has a day off on Thursday. Finally, constraint (18) ensures that if a driver has a day off on Friday that he is not allowed to work on the following Saturday.

Constraint (19) ensures that shifts, combinations of a tank truck and a shift type, are not assigned to non-qualified drivers for those shifts. Constraint (20) imposes that the decision variable assigning a shift to a driver on a given day is only allowed to take the values 0 and 1 and therefore has a binary character. Similarly, v_{jw}^1 and v_{jw}^2 have a binary character imposed by constraint (21). Last, constraint (22) ensures that D_j^+ and D_j^- are greater than or equal to 0.

As cited in Section 2, an additional constraint needs to be introduced in order to analyse the trade-off between the costs and the employees' preferences. The cost component consists of the extra (variable) costs on top of the basic (fixed) salary that must be paid to the permanent as well as the extra costs on top of the contractually agreed cap Z_j^{max} for the temporary drivers and a part for violations related to less preferred drivers assigned to the tank trucks. The preference component takes into account the overtime preference for the permanent drivers. For this purpose, constraint (23) is formulated. This constraint ensures that the overtime of the company's own staff, the permanent drivers, is less than or equal to a certain predefined number of overtime hours X. By examining different values for X, the impact of preference violations on the costs can be observed.

4.3. Data inputs

To run the presented model, the real-world data from the oil company reported in Knust and Schumacher (2011) will mainly be used. In this section, the values of the data components are specified.

The scheduling problem consists of 30 drivers, made up of 25 permanent drivers and 5 temporary drivers. Due to personal circumstances, drivers 12 and 21 should not have the same type of shift in two consecutive weeks. In addition, the oil company has a total of 17 tank trucks at its disposal. These trucks are assigned to shifts, with a shift length l_t = 10 hours from Monday to Friday and a shift length l_t = 5 hours on Saturdays. For these 17 available trucks, a list of qualified drivers is also provided in Table 7 which ranks the drivers for each truck from most suitable to least suitable. The suitability coefficients $\alpha_{jv} = 0$ for the most suitable driver (i.e., the first in line), followed by $\alpha_{jv} \in \{0.1, 0.2, 0.3\}$ for the other suitable drivers. Besides these qualified drivers, it is also possible to have some additional acceptable drivers for some trucks (Knust & Schumacher, 2011). These extra drivers are assigned a suitability coefficient $\alpha_{jv} = 0.5$ and are employable in both early and late shifts.

A time span of one month is included in the scheduling model. The monthly working time interval $[Z_j^{min}, Z_j^{max}]$ of the permanent drivers is set to $[180, 180]$, with the exception of driver 24. This driver is assigned a working time interval of $[0, 50]$ as he is only a jumper for one tank truck (Knust & Schumacher, 2011). The temporary drivers are allocated a working time interval of $[0, 50]$, except for drivers 28 and 29. These two drivers are assigned a working time interval of only $[0, 20]$ as they are only available on Saturdays.

Table 7 List of qualified drivers for each tank truck (based on Knust and Schumacher (2011))

Tank truck	Early shift drivers	Late shift drivers	Extra drivers
1	13,8,9,26	16,8,9,26	27,28,29,19
2	19,9,8,26	14,9,8,26	27,28,13,16,29,21
3	21,12,8,9	12,21,8,9	27,28,29
4	23,8,9,26		3,27,28,15,29
5	20,5,15,26		3,27,6
6	4,7,22,10		
7	-,15,9,20		
8	11,5,15,26		
9	3,15,5,26		
10	17,15,27,1		
11	2,7,10,26		
12	25,15,17,20		1,27,9
13	10,7,26,2		
14	6,15,5,26		27
15	22,7,4,10		
16	1,15,25,20		
17	18,24,26,30		

Finally, values are also assigned to the penalty cost factors w_j^+, w_j^- and $\widehat{w_j}$ present in the objective function. As discussed earlier, w_j^- is assigned a value of 0 for all drivers. Concerning w_j^+, permanent drivers are given a value of 10; temporary drivers a value of 20 and the dummy driver a value of 10 000. This large value for the dummy driver was chosen to avoid shift allocations as this would result in a lower service level. However, this value does not reflect the actual cost for a non carried out shift since we did not have this information available. Furthermore, the factor $\widehat{w_j}$ is assigned a value of 3 for all permanent drivers and a value of 1 for the temporary drivers.

In the following section, the results are presented with respect to the model that has just been described. To be able to obtain some results, the personnel scheduling model and the corresponding real-world data has been implemented into the mathematical programming language AMPL, which offers a sophisticated modelling tool for optimisation problems (AMPL). In order to support the implementation of the model and data in AMPL, the following sources were mainly consulted; Fourer, Gay, and Kernighan (2003a, 2003b, 2003c, 2003d, 2003e, 2003f, 2003g)

5. Results

In order to gain insights into the trade-off aspect between personnel costs and employee preferences, several analyses were conducted.

The first analysis is conducted to investigate the impact on personnel costs in case more flexibility is demanded from the oil company's own personnel (i.e., the permanent drivers). The type of flexibility focused on in this analysis is the allocation of a particular maximum amount of overtime to the permanent drivers. To obtain the trade-off aspect, various data points need to be identified. However, from the computational results obtained, it emerged that only certain discrete points can be used to construct the trade-off curve. Thereby, the following situations are considered; no overtime allowed and maximum 5, 10, 15 and 20 hours overtime allowed for each of the permanent drivers. The underlying reason for analysing in 5-hour time intervals lies in the fact that no changes take place when intervals are chosen which are no multiplications of 5. This can be explained by the fact that the personnel scheduling model only allocates shifts of 5 and 10 hours to the drivers and, in doing so, only allows the allocation of a full shift to one driver. For instance, a permanent driver who already works 180 hours by default in the 'no overtime allowed' scenario cannot be given an extra full shift if the number of overtime hours allowed only increases by for example two or four hours. However, an increase of 5 hours is sufficient to enable the driver to work an additional Saturday shift of 5 hours. Once an increase of 10 hours has been agreed, an extra shift on weekdays can be covered by the permanent driver.

In reality, however, it is generally the case that overtime is assigned on an ad hoc basis. Some days/ weeks, an employee may not work overtime, but other days/weeks he or she does. The number of overtime hours allocated to an employee can also vary enormously by day/week and is not restricted to multiples of 5 hours. It is therefore important to bear in mind, when interpreting the results, that this ad hoc aspect is not entirely present. The absence can also be partly explained by the context of the model. Within the oil company, the tank trucks have to cover trips to and from particular destinations. The difference in location of drivers makes the random, continuous allocation of overtime in this particular context difficult. For example, you cannot expect driver A to cover the first two hours of a trip to a particular destination and driver B to cover the remaining hours of the shift and thus complete the trip. In a nursing context, for example, it can happen that nurse A works two extra hours of another shift in overtime, while nurse B can take care of the remaining hours of that shift. Hence, in this analysis overtime will always be allocated in multiples of 5.

Besides, we have chosen to show only up to a maximum of 20 allowed overtime hours in the trade-off curve in Figure 2. The analysis results showed that as soon as each of the permanent drivers were asked to work a maximum of 10 overtime hours, all overtime hours were handled again by them. No temporary drivers were hired for overtime. Given an allocation of 15 overtime hours or more, the trade-off curve flattens out significantly. This can be attributed to the two-part structure of the objective function of the personnel scheduling model. As mentioned earlier, the objective function penalises each violation of the soft constraints (S1) and (S2) from Table 6. Assigning 15 or more overtime hours, only results in minor changes with respect to the second soft constraint. Most likely, shifts are assigned in overtime to a more feasible driver than previously. No changes in costs occur concerning the first soft constraint (S1), since all overtime hours remain handled by the permanent drivers starting from an allocation of 10 overtime hours and more. When no overtime hours are allowed for permanent drivers or only 5 overtime hours, a large proportion of the shifts still to be covered are handled by the temporary drivers. In these scenarios, 170 and 130 overtime hours respectively were still performed by the temporary drivers.

Furthermore, it is important to note that only the extra personnel costs are taken into account on the y-axis. The fixed salary costs for the stipulated 180 working hours for the permanent drivers are not included in the trade-off curve. This is due to the fact that it concerns a fixed amount which the company has to pay anyway, regardless of the actual number of hours worked. Besides, the performed hours falling in the monthly working time interval $[Z_j^{min}, Z_j^{max}]$ for the temporary drivers are also not included in the trade-off curve. This is due to the fact that it concerns a certain contractually predetermined amount that the company has to pay to its subcontractor. It is also important to mention that these additional personnel costs involve all drivers, i.e., both permanent and temporary drivers. If there are shift allocations to the dummy driver, the costs related to this dummy driver are zero; as these allocations refer to shifts that are not actually carried out, it results in a lower service level (shown on the secondary axis). The x-axis, on the other hand, only shows the maximum overtime allowed for each permanent driver over the time span of one month.

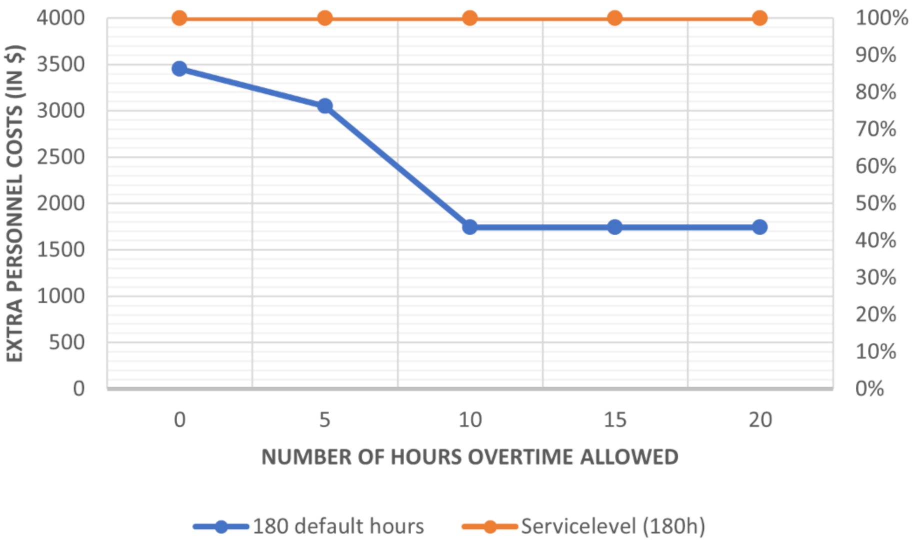

Figure 2 Trade-off between personnel costs and overtime preference violations, for 180 standard hours

It can be seen from Figure 2 and Table 8 that the personnel costs decrease when the number of allowed overtime hours for permanent drivers increases. In the first scenario, where the aim is to perfectly satisfy the overtime preference of the own personnel (i.e., no overtime allowed for each permanent driver), the additional personnel costs were assigned an amount of $3448.50. A cost of $3400 relates to the first soft constraint (S1) and a cost of $48.50 to the second soft constraint (S2). The second scenario allows a saving of $400 regarding the first soft constraint (S1) compared to the first scenario. This saving is achieved by reducing the temporary drivers' hours by 40. This yields a cost reduction of 40 times $20. However, it has to be added that these 40 overtime hours are taken over by the permanent drivers by assigning 5 overtime hours to 8 permanent drivers. The cost of doing this amounts to 40 times $10. Taken together, this provides a saving of $800 minus $400 which gives $400. With regard to the second constraint (S2), a small increase in costs is observed of $1. The most substantial reduction in costs of 42.80% is obtained when imposing an overtime preference violation of 10 hours. In this case, the costs obtained in the first scenario (i.e., no overtime allowed) decrease by 49.42%, resulting in a personnel cost of $1744.30 divided into $1700 for soft constraint (S1) and $44.30 for soft constraint (S2). The cost of $1700 can be attributed to the fact that 17 permanent drivers are granted 10 overtime hours at a price of $10 per overtime hour. No temporary drivers were hired for overtime. The further imposition of 15 and 20 overtime hours only leads to a further decrease in the personnel costs of less than 1%, as can be seen from Table 8. It can therefore be stated that a sufficient reduction in the costs is no longer obtained to motivate a preference violation above 10 hours, as the percentage changes for these scenarios are negligible.

Table 8 Percentage differences in personnel costs (180 standard hours)

Scenario	Number of hours overtime allowed	Extra personnel costs (in $)	Percentage difference relative to scenario 1	Percentage difference relative to previous scenario
1	0	3448.50		
2	5	3049.50	- 11.57%	- 11.57%
3	10	1744.30	- 49.42%	- 42.80%
4	15	1743.70	- 49.44%	- 0.03%
5	20	1742.30	- 49.48%	- 0.08%

In addition, all 5 scenarios allow all shifts to be driven by either permanent or temporary drivers. No shift allocation to the dummy driver is required, resulting in a 100% service level at the current standard hours (i.e., in general an interval of $[180, 180]$ for the permanent drivers and an interval of $[0, 50]$ for the temporary drivers). To conclude, there is a trade-off mechanism playing between the fulfilment of employee preferences and the related personnel costs. A reduction of approximately one half of the personnel costs is achievable by imposing a minimum requirement of 10 overtime hours for the permanent drivers. However, if the company, either in consultation with the permanent drivers or not, finds this imposition unacceptable, it is still possible to reduce personnel costs by approximately 12% with a maximum of 5 overtime hours. Lastly, the presence of a flattening is observed as soon as all the overtime can be taken up again by the company's own personnel. This is due to the fact that all potential cost savings related to the working time intervals of the drivers (S1) have been obtained. Further changes can only occur with regard to the suitability of a driver (S2).

To be able to analyse the trade-off aspect in more depth with more data points, it was opted to run the same analysis but with a change in the working time interval of the permanent drivers. Instead of a monthly working time interval of $[180, 180]$, this analysis assumes a working time interval of $[170, 170]$. However, permanent driver 24 retains his limited working time interval of $[0, 50]$; also, the working time interval of the temporary drivers will not be changed. This enabled the following situations to be investigated; no overtime allowed and maximum 5, 10, 15, 20, 25 and 30 hours overtime allowed for each of the permanent drivers. As can be seen in Figure 3, the decrease in the number of standard hours to $[170, 170]$ shows the same trend but with a noticeable shift upward (i.e., we have higher personnel costs in total, which is logical as more trips will have to be covered in overtime). Here, all overtime hours are handled again by the permanent drivers from an allocation of 20 overtime hours per permanent driver. From then on, the remaining changes in the additional personnel costs are attributed to the second soft constraint (S2) whereby shifts are assigned to more suitable permanent drivers. Hence, it can be stated that demanding more than 20 overtime hours from each permanent driver is not cost-effective as the percentage changes in Table 9 for these scenarios are negligible.

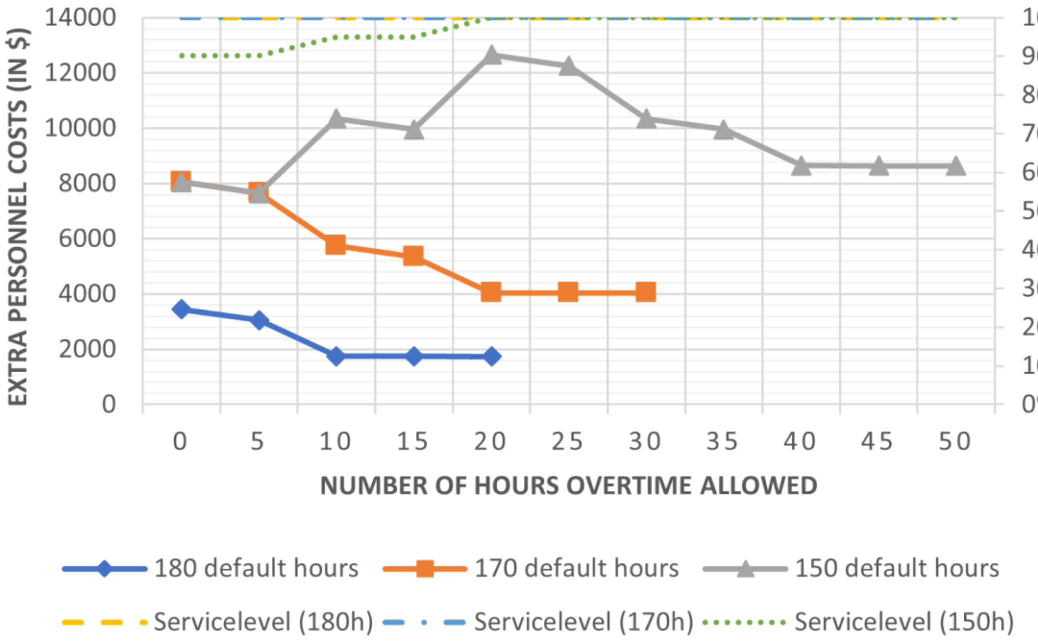

Figure 3 Trade-off comparison between the 3 settings

Moreover, on the secondary axis of Figure 3, it can be seen from the blue dashed line that the service level at 170 standard hours remains at 100%. All the shifts are consequently handled by either permanent or temporary drivers. No shift was assigned to the dummy driver in the personnel scheduling model, meaning that no demand remained uncovered. The additional personnel costs in the first scenario (i.e., no overtime allowed) were assigned an amount of $8055.90. A cost of $8000 relates to the first soft constraint (S1) and a cost of $55.90 to the second soft constraint (S2). Reducing the number of standard hours for the permanent drivers by 10 hours (i.e., from 180 to 170 standard hours) results in a significant increase of the additional personnel costs. Regarding the first scenario, this represents a percentage increase of 133.61% (as more trips are covered in overtime).

Furthermore, substantial cost savings of about 25% are achieved when switching to 10 (scenario 3) and to 20 (scenario 5) maximum allowable overtime hours for each permanent driver as can be seen in Table 9. The largest part of this saving is related to the first soft constraint (S1). In scenario 3, 190 overtime hours are switched from temporary drivers to the permanent drivers. On the one hand, costs are reduced by 190 times $20. While on the other hand, a cost of 190 times $10 should be added. Taken together, this provides a saving of $3800 minus $1900 which gives $1900. The remaining saving of $6.2

relates to the second soft constraint (S2), indicating assignments of shifts to more suitable drivers. The same reasoning is followed when shifting to scenario 5, in which 130 overtime hours are switched.

Table 9 Percentage differences in personnel costs (170 standard hours)

Scenario	Number of hours overtime allowed	Extra personnel costs (in $)	Percentage difference relative to scenario 1	Percentage difference relative to previous scenario
1	0	8055.90		
2	5	7655.10	- 4.98%	- 4.98%
3	10	5748.90	- 28.64%	- 24.90%
4	15	5349.80	- 33.59%	- 6.94%
5	20	4044.30	- 49.80%	- 24.40%
6	25	4043.40	- 49.81%	- 0.02%
7	30	4040.40	- 49.85%	- 0.07%

In both settings so far (i.e., 180 and 170 standard hours) all shifts are covered by either temporary or permanent drivers. No shifts were assigned to the dummy driver, resulting in a 100% service level. In order to include the effect of a changing service level in the trade-off analyses, the monthly working time interval is adjusted to $[150, 150]$. Again, permanent driver 24 retains his limited working time interval of $[0, 50]$, as well as the working time interval of the temporary drivers will not be changed. This enabled the following situations to be investigated; no overtime allowed and maximum 5, 10, 15, 20, 25, 30, 35, 40, 45 and 50 hours overtime allowed for each of the permanent drivers.

As can be seen from the green dashed line in Figure 3, not all shifts are covered in 4 scenarios where the number of standard hours is set equal to 150. These scenarios are (1) no overtime allowed, (2) up to 5 overtime hours allowed, (3) up to 10 overtime hours allowed and (4) up to 15 overtime hours allowed for each permanent driver. In the first two scenarios, a service level of 90.17% can be achieved. This means that the oil company will be able to cover 4220 hours out of the total 4680 hours to be covered. The remaining 460 hours are allocated to the dummy driver for two reasons. Firstly, there are no permanent drivers with free hours available or with the right suitability to take on an extra shifts. Secondly, there are no temporary drivers who are feasible drivers for the trucks of the shifts still to be covered. In the third and fourth scenarios, there is a 95.09% service level. More specifically, 4450 of the 4680 hours are actually performed by the permanent and/or temporary drivers. Only 230 hours are allocated to the dummy driver for the same two reasons as mentioned previously. For scenarios 5 to 11 listed in Table 10, a service level of 100% is achieved and consequently all shifts are covered again.

Table 10 Percentage differences in personnel costs (150 standard hours)

Scenario	Number of hours overtime allowed	Extra personnel costs (in $)	Percentage difference relative to scenario 1	Percentage difference relative to previous scenario
1	0	8047.60		
2	5	7646.20	- 4.97%	- 4.97%
3	10	10350.70	28.57%	35.29%
4	15	9949.90	23.71%	- 3.78%
5	20	12657.10	57.23%	27.09%
6	25	12255.40	52.24%	- 3.17%
7	30	10349.20	28.56%	- 15.55%
8	35	9950.40	23.61%	- 3.85%
9	40	8644.60	7.39%	- 13.12%
10	45	8643.30	7.37%	- 0.02%
11	50	8638.6	7.31%	- 0.05%

In the first scenario (i.e., no overtime allowed for each permanent driver), the additional personnel costs were assigned an amount of $8047.60. A cost of $8000 relates to the first soft constraint (S1), whereby no overtime hours are driven by the permanent drivers and 400 overtime hours are driven by the temporary drivers at a cost of $20 per overtime hour. Furthermore, a cost of $47.60 is related to the second soft constraint (S2). The second scenario allows a saving of 4.97% equivalent to an amount of $401.4. The shift to the third scenario implies a cost increase of $2704.5. This is due to the fact that the dummy driver is not assigned 460 hours anymore, but only 230 hours. The permanent and temporary drivers can again cover the other 230 hours. A cost increase was therefore accepted in exchange for an improved service level of 95.09%. The same trend can be observed in the switch from scenario 4 to 5. Here, the remaining 230 hours allocated to the dummy driver are also shifted to the permanent and temporary drivers. Again, it results in a cost increase but in return a 100% service level is achieved. From scenario 5 onwards, costs decrease because the permanent drivers gradually take over more overtime hours from the temporary drivers resulting in a lower cost per overtime hour for the company. As soon as a maximum of 40 overtime hours is allowed per permanent driver, the trade-off curve flattens out significantly. Accordingly, no temporary drivers are hired for overtime and consequently all overtime is handled again by the permanent drivers. Assigning 40 or more overtime hours therefore only results in minor changes with respect to the second soft constraint. Most likely, shifts are assigned in overtime to a more feasible driver than previously. Hence, it can be stated that demanding more than 40 overtime hours from each permanent driver is not cost-effective as the percentage changes in Table 10 for these scenarios are negligible (< 1%). Finally, a trade-off may arise in which one wants to give in on the service level in return for a lower workload for the employees and hence lower additional personnel costs.

From the results of the personnel scheduling model, another interesting insight can be drawn regarding the flexible use of capacity. The small oil company owns 17 different types of tank trucks and 30 drivers divided into 25 permanent and 5 temporary drivers. Evidently, the company has to make decisions about which driver to train for which trucks. How much flexibility is needed in order to have sufficient capacity utilisation benefits? As Jordan and Graves (1995) state, it is possible to gain the benefits of total flexibility through limited cross-training of the employees and thus by only slightly increasing flexibility. Total flexibility in the case of the oil company would imply training every driver for every truck. However, at the moment the company doesn't have this full flexibility (see Table 7), and achieving this full flexibility would be unnecessarily costly. Jordan and Graves (1995) discovered that the concept of *chaining* is important to decide where the flexibility should be added: the goal should be to create big pools of drivers (and associated trucks), in such a way that work can be shifted between the members of the pool (note that this doesn't mean that all drivers need to be able to handle all trucks; they just need to be able to hand over work to someone else, in case of high demand). Such a group of trucks and drivers that are, directly or indirectly, connected to each other by potential assignment decisions, is referred to as a *chain*. The researchers give as a guideline that the most effective way to add flexibility is to create fewer and longer chains (Jordan & Graves, 1995).

Table 11 Shifting of hours worked by adding flexibility

Base situation			**Flexibility added**		
Drivers	Hours worked	Z_j^{max}	Drivers	Hours worked	Z_j^{max}
Driver 24 (P)	20	50	Driver 24 (P)	**50**	50
Driver 26 (T)	70	50	Driver 26 (T)	70	50
Driver 27 (T)	200	50	Driver 27 (T)	**150**	50
Driver 28 (T)	20	20	Driver 28 (T)	20	20
Driver 29 (T)	20	20	Driver 29 (T)	20	20
Driver 30 (T)	30	50	Driver 30 (T)	**50**	50

* P = permanent driver, T = temporary driver

Take, for instance, the setting with 180 standard hours where no overtime may be allocated to the permanent drivers. We can then examine which temporary drivers work a lot of overtime hours, and which work less than can be expected. As can be seen from Table 11, drivers 26 and 27 work 20 and 150 overtime hours respectively in the base situation. While temporary driver 30 works 20 hours less than can be expected. Of the permanent drivers, all drivers work their expected 180 hours except driver 24. Driver 24 is only a jumper for tank truck 17, and therefore has a working time of only 50 hours. As can be seen from Table 11, he is only working 20 of his 50 paid hours. It would therefore be possible to realise an improvement in the allocation of the shifts by adding limited flexibility/cross-training throughout creating a (longer) chain between drivers 24, 26, 27 and 30 (24 and 30 are “underutilized”, while 26 and 27 have too much work to take care of).

To be able to establish this (longer) chain, modifications are made in the personnel scheduling model in Section 4: we make driver 30 feasible for the tank trucks of drivers 26 and 27, such that driver 30 can take over workload from them. For the purposes of this analysis, we keep permanent driver 24 as a jumper for one truck only. We then analysed the 12 scenarios in which each considered truck is made feasible independently and subsequently the option in which all 12 possible tank trucks are jointly made feasible for driver 30 as can be seen in Table 12. Hence, a suitability coefficient of $\alpha_{30v} = 0.5$ is given for v = 1, 2, 3, 4, 5, 8, 9, 10, 11, 12, 13 and 14.

Table 12 Flexibility configurations and the corresponding additional personnel costs

Added connection	Additional costs (in $)	Added connection	Additional costs (in $)
Truck 1 – Driver 30	2449.7	Truck 9 – Driver 30	2450.5
Truck 2 – Driver 30	2449.6	Truck 10 – Driver 30	2449.8
Truck 3 – Driver 30	2448.5	Truck 11 – Driver 30	3048.9
Truck 4 – Driver 30	2449.7	**Truck 12 – Driver 30**	**2448.3**
Truck 5 – Driver 30	2452	Truck 13 – Driver 30	3049.2
Truck 8 – Driver 30	2452	Truck 14 – Driver 30	2450.5
Truck 1, 2, 3, 4, 5, 8, 9, 10, 11, 12, 13, 14 – Driver 30 (full flexibility)	2448.4		

Table 12 reveals that the single allocation of tank truck v = 12 to driver 30 yields the lowest additional personnel costs of $2448.3. In other words, the cross-training of driver 30 for tank truck 12 should cost at most $1000.2 ($3448.5 - $2448.3) for the oil company to remain at break-even. Moreover, it virtually coincides with the gain that could be realized when the driver was cross-trained to handle *all* trucks (see Table 12, full flexibility). This again relies on the insight from Jordan and Graves (1995) that adding limited flexibility (i.e. 1 connection for driver 30) can achieve about the same benefits as total flexibility (i.e. all truck connections for driver 30). Note that the realized gain is more or less equal for many other kinds of trucks. Exceptions are truck 11 and 13, where only 20 overtime hours could be transferred. For all other trucks, it was possible to shift a total of 50 overtime hours.

It can be seen from Table 11 in the column 'Flexibility added' that temporary driver 27 now works 100 overtime hours instead of the 150 overtime hours in the base situation. In addition, both drivers 24 and 30 now work their stipulated 50 hours, taking over 50 overtime hours from driver 27. As can be derived from Table 13, by adding the connection 'Truck 12 – Driver 30', driver 27 transfers five 10-hour shifts for truck 12 to driver 30. However, because driver 24 is connected to driver 30 through a chain, driver 24 now covers the three 'base' shifts of driver 30. This way, even with just one extra training course for driver 30, significant shifts in workload can be obtained.

Table 13 Shift configurations between drivers 24 and 30

Base situation	
Driver 24	Driver 30
10h-shift – Truck 17	**10h-shift – Truck 17**
10h-shift – Truck 17	**10h-shift – Truck 17**
	10h-shift – Truck 17
Flexibility added	
Driver 24	Driver 30
10h-shift – Truck 17	10h-shift – Truck 12
10h-shift – Truck 17	10h-shift – Truck 12
10h-shift – Truck 17	10h-shift – Truck 12
10h-shift – Truck 17	10h-shift – Truck 12
10h-shift – Truck 17	10h-shift – Truck 12

In conclusion, it can be said that by increasing the flexibility of the workforce capacity slightly, a cost benefit can be obtained. However, as pointed out by Jordan and Graves (1995), it is important to add the flexibility in the right place. This can be seen in Table 12, as not every new connection resulted in the same cost advantage. The explanation of this is related to the concept of *chaining* (Jordan & Graves, 1995). After all, one makes better use of its existing capacity when there are longer and fewer chains between the trucks and drivers. This leads to more possibilities for workload shifting, as just discussed for driver 30.

6. Conclusions and insights

In this article, we reviewed the research papers in Van den Bergh et al. (2013) that address employees' preferences using mathematical programming as solution technique. Additionally, the resulting classification tables in Section 3 allowed to analyse which characteristics are most prominent.

Researchers have become very inventive in applying highly divergent methodologies to optimise employees' preferences in personnel scheduling models, and thus meet a multitude of objectives and constraints. Unfortunately, the underlying assumptions of the methodologies all to often reveal that the developed models rely on quite abstract assumptions (e.g., homogeneity of employees, the use of theoretical inputs, and the coalition formation within the multi-agent approach). As we observed in Table 3, many models lack a real-life implementation. The few research papers that do involve a real-life implementation followed a trial-and-error strategy during model development, thereby making implicit knowledge become explicit and obtaining models that are more realistic and more applicable in practice.

The results of the literature review showed that only a few researchers have tried to tackle the interplay between the personnel costs and employees' preferences (Bard & Purnomo, 2005; Wright & Bretthauer, 2010; Wright et al., 2006); however, none of them addressed this trade-off relationship as a main conclusion of their research, despite the relevance of this subject in many real-life situations. In this thesis, the personnel scheduling model, provided by Knust and Schumacher (2011), is used as a starting point to capture this trade-off, along with the case data this paper provided for a real life oil company. The main question is; 'If the preferences of the employees are violated to a certain level, what cost saving is gained in return?'. The experimental results showed that the extent to which a trade-off appears between personnel costs and employees' preferences is primarily related to the cost differential that is present between the various types of capacity. The use of two types of capacity, temporary and permanent truck drivers, is examined in the oil company's case. Consequently, fulfilling more preferences of the permanent drivers leads to less flexibility in designing a personnel schedule. As a result, more workload will be put on other available types of capacity (temporary drivers). It is therefore apparent that a significant cost differential will have a major impact on the acquired personnel costs. Moreover, if total capacity is insufficient, part of the demand remains uncovered.

An important challenge for the trade-off analysis between the personnel costs and the employees' preferences is the way in which associated constraints are modelled. We emphasize that the accuracy of the trade-off lies in the ability of the constraints to provide enough meaningful solution points. As discussed in Section 5, the constraints of the case problem only allow for the allocation of full 5 and 10-hour shifts. The inclusion of an ad hoc allocation thus remains a considerable opportunity for further research. On the other hand, the constraints also specify that the temporary drivers have a 50-hour contract, whereby any amount above this limit is classified as overtime. Care should be taken when formulating such constraints, as they impact the shape of the resulting trade-off.

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Personnel scheduling: studying the trade-off between personnel costs and employee preferences
Promotor: Prof. Dr. Inneke Van Nieuwenhuyse
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Bibliography

AMPL. Retrieved from https://ampl.com/

Balaji, P., & Srinivasan, D. (2010). An introduction to multi-agent systems. In *Innovations in multi-agent systems and applications-1* (pp. 1-27): Springer.

Bard, J. F., & Purnomo, H. W. (2005). Short-Term Nurse Scheduling in Response to Daily Fluctuations in Supply and Demand. *Health care management science, 8*(4), 315-324. doi:10.1007/s10729-005-4141-9

Cohn, A., Root, S., Esses, J., Kymissis, C., & Westmoreland, N. (2006). Using mathematical programming to schedule medical residents. *Boston University School of Medicine, Boston, MA*.

Ernst et al., A. T. (2004). Staff scheduling and rostering: A review of applications, methods and models. *European journal of operational research, 153*(1), 3-27. doi:10.1016/S0377-2217(03)00095-X

Fourer, R., Gay, D. M., & Kernighan, B. W. (2003a). Command Scripts. In *AMPL: A Modeling Language for Mathematical Programming*.

Fourer, R., Gay, D. M., & Kernighan, B. W. (2003b). Integer Linear Programs. In *AMPL: A Modeling Language for Mathematical Programming*.

Fourer, R., Gay, D. M., & Kernighan, B. W. (2003c). Linear Programs: Variables, Objectives and Constraints. In *AMPL: A Modeling Language for Mathematical Programming*.

Fourer, R., Gay, D. M., & Kernighan, B. W. (2003d). Modeling Commands. In *AMPL: A Modeling Language for Mathematical Programming*.

Fourer, R., Gay, D. M., & Kernighan, B. W. (2003e). Parameters and Expressions. In *AMPL: A Modeling Language for Mathematical Programming*.

Fourer, R., Gay, D. M., & Kernighan, B. W. (2003f). Production Models: Maximizing Profits. In *AMPL: A Modeling Language for Mathematical Programming*.

Fourer, R., Gay, D. M., & Kernighan, B. W. (2003g). Specifying Data. In *AMPL: A Modeling Language for Mathematical Programming*.

Gordon, L., & Erkut, E. (2004). Improving Volunteer Scheduling for the Edmonton Folk Festival. *Interfaces (Providence), 34*(5), 367-376. doi:10.1287/inte.1040.0097

Jordan, W. C., & Graves, S. C. (1995). Principles on the Benefits of Manufacturing Process Flexibility. *Management science, 41*(4), 577-594. doi:10.1287/mnsc.41.4.577

Knust, S., & Schumacher, E. (2011). Shift scheduling for tank trucks. *Omega (Oxford), 39*(5), 513-521. doi:10.1016/j.omega.2010.10.009

Pastor, R., & Corominas, A. (2010). A bicriteria integer programming model for the hierarchical workforce scheduling problem. *Journal of modelling in management, 5*(1), 54-62. doi:10.1108/17465661011026167

Paycor. (2020, 24 December 2020). The biggest cost of doing business: a closer look at labor costs. Retrieved from https://www.paycor.com/resource-center/articles/the-biggest-cost-of-doing-business-a-closer-look-at-labor-costs/

Sabar, M., Montreuil, B., & Frayret, J. M. (2008). Competency and preference based personnel scheduling in large assembly lines. *International journal of computer integrated manufacturing, 21*(4), 468-479. doi:10.1080/09511920701574842

Sabar, M., Montreuil, B., & Frayret, J. M. (2009). A multi-agent-based approach for personnel scheduling in assembly centers. *Engineering applications of artificial intelligence, 22*(7), 1080-1088. doi:10.1016/j.engappai.2009.02.009

Stolletz, R., & Brunner, J. O. (2012). Fair optimization of fortnightly physician schedules with flexible shifts. *European journal of operational research, 219*(3), 622-629. doi:10.1016/j.ejor.2011.10.038

Topaloglu, S., & Ozkarahan, I. (2004). An Implicit Goal Programming Model for the Tour Scheduling Problem Considering the Employee Work Preferences. *Annals of operations research, 128*(1), 135-158. doi:10.1023/B:ANOR.0000019102.68222.df

Ulusam Seçkiner, S., Gökçen, H., & Kurt, M. (2007). An integer programming model for hierarchical workforce scheduling problem. *European journal of operational research, 183*(2), 694-699. doi:10.1016/j.ejor.2006.10.030

Valouxis, C., Gogos, C., Goulas, G., Alefragis, P., & Housos, E. (2012). A systematic two phase approach for the nurse rostering problem. *European journal of operational research, 219*(2), 425-433. doi:10.1016/j.ejor.2011.12.042

Van den Bergh et al., J. (2013). Personnel scheduling: A literature review. *European journal of operational research*, *226*(3), 367-385. doi:10.1016/j.ejor.2012.11.029

Wooldridge, M. (2009). *An introduction to multiagent systems*: John wiley & sons.

Wooldridge, M., & Jennings, N. R. (1995). Intelligent agents: Theory and practice. *The knowledge engineering review, 10*(2), 115-152.

Wright, P. D., & Bretthauer, K. M. (2010). Strategies for Addressing the Nursing Shortage: Coordinated Decision Making and Workforce Flexibility. *Decision sciences, 41*(2), 373-401. doi:10.1111/j.1540-5915.2010.00269.x

Wright, P. D., Bretthauer, K. M., & Côté, M. J. (2006). Reexamining the Nurse Scheduling Problem: Staffing Ratios and Nursing Shortages. *Decision sciences, 37*(1), 39-70. doi:10.1111/j.1540-5414.2006.00109.x