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Fairness Aspects in Personnel Scheduling

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In industries like health care, public transport or call centers a shift-based system ensures permanent availability of employees for covering needed services. The resource allocation problem – assigning employees to shifts – is known as personnel scheduling in literature and often aims at minimizing staffing costs. Working in shifts, though, impacts employees' private lives which adds to the problem of increasing staff shortage in recent years. Therefore, more and more effort is spent on incorporating fairness into scheduling approaches in order to increase employees' satisfaction. This paper presents a literature review of approaches for personnel scheduling considering fairness aspects. Since fairness is not a quantitative objective, but can be evaluated from different point of views, a large number of fairness measurements exists in the literature. Furthermore, perspective (group vs individual fairness) or time horizon (short-term vs long-term fairness) are often considered very differently. To conclude, we show that a uniform definition and approach for considering fairness in personnel scheduling is challenging and point out gaps for future research.

Keywords Long-Term Fairness · Preference Scheduling · Optimization · Literature Review

1 Introduction and Motivation

More than 20% of European workers are employed in a shift-based system (Harrington, 2001). In industries like health care, public transport or call centers, for example, a shift-based system ensures permanent availability of services. Therefore, several shifts are defined. Usually a shift lasts between six and twelve hours leading to two to four different shift types a day (Harrington, 2001). Working in shifts often comes along with changing working hours that have a great impact on private life. With staff shortage increasing in the last years, it is tried to improve shift working conditions. The acceptance of schedules is essential for a successful operation and long-term satisfaction of employees working in shifts. Effects of schedules perceived as unfair include: decreased job satisfaction, lower job performance, bickering, increased absenteeism, increased turnover rates and trigger of labor strikes (Bard & Purnomo, 2005a; Abbink et al., 2005). In order to prevent such consequences, the allocation of human resources should take fairness aspects into account.

A definition of a fair resource allocation is difficult as it depends on the circumstances of the situation of the affected resources as well as the allocation which is evaluated. Different aspects of fairness may be relevant depending on the allocation problem. Nevertheless, various concepts and evaluation criteria for a fair resource allocation have been proposed in recent years (Karsu & Morton, 2015). When personnel is the resource to be allocated, fairness aspects seem to be quite relevant, because human perceptions, emotions and reactions go far beyond those of machines. For example, an individual consideration of each resource might be more important than complete equal treatment.

Personnel scheduling denotes the task of assigning employees to shifts or vice versa for a fixed planning period in order to provide the right amount of personnel at the right time. Usually, the most common objective is to minimize operational personnel costs. This complex task is executed manually or using a decision support system. The consideration of fairness is an ongoing problem by personnel scheduling, since particular attention must be paid to the well-being of employees when they are assigned to shifts. Many schedules now aim to consider fairness requirements, such as taking into account individual preferences and requests in an equitable manner. This increases the complexity of the decision problem due to the resulting trade-off between efficiency and fairness, as a cost minimal schedule does often not provide the highest fairness. However, solution approaches differ greatly in their implementation of fairness.

We define three key questions that are discussed in this paper:

(i) What is fairness in the context of resource allocation?

(ii) Which fairness aspects are important in personnel scheduling?

(iii) Which approaches exist to include fairness as an optimization objective for personnel scheduling?

The paper is organized along addressing these questions. The first question addresses the definition of fairness. Therefore, section 2 provides a brief overview on fairness in general, perspectives on fairness and several fairness measures. To answer the second question, we discuss fairness in the context of shift work in section 3. We prescribe the decision problems associated with shift work in the planning process and fairness issues arising in it. The third question implies that fairness can be quantified differently for consideration in an objective function of an optimization model. In addition, various solution approaches have been developed. We provide a detailed description and discussion of these approaches in section 4. We conclude the paper in section 5 by summarizing the review and pointing out future research directions.

2 Notion of Fairness in Resource Allocation

Fairness is an important criterion for the evaluation of resource allocations. An equal distribution of resources is closely linked to the definition of fairness. Shi et al. (2014) differentiate between targeted fairness aiming at a fair resource allocation and resultant fairness addressing a fair utilization of resources. In the evaluation of the allocation itself, only the outcome is assessed. Thereby, the decision-making process is not taken into account. If the resource allocation decisions are made fairly, it is likely that the outcome will also be fair. In the following, we capture fairness by resultant fairness, since we assume that a fair outcome is achieved through a fair procedure.

The intention to define fairness rationally implies that it is possible to allocate resources fairly (Hufnagel & Birnberg, 1989). However, this requires an understanding of fairness. The meaning of fairness has been largely studied in the economics and psychological literature. Nevertheless, a universal definition of fairness is hardly possible if not useless, as circumstances have a great influence on the definition. Each resource allocation may focus on different fairness and equity aspects and which allocation people perceive as fair is based on subjective interpretation. In general, an envy-free allocation of resources is close to a fair allocation. But Holcombe (1997) discusses the challenging task of defining an envy-free outcome considering the fact that people evaluate fairness differently depending on their commitment. Thus, an unequal distribution of resources can also be evaluated as fair. Two slightly different approaches are, for example, total equity, in which each individual is treated exactly the same, and compensation for effort, in which resources are allocated depending on the individual contribution. Hufnagel & Birnberg (1989) make similar conclusions by stating that allocative equity is based in particular on subjective perception. This discussion leads to two distinct angles from which fairness can be assessed.

Perspective of Fairness The judgment of a resource allocation's fairness can be done from the perspective of the whole group or from an individual point of view. Shi et al. (2014) define *group fairness* as a state in which all individuals are treated equally. In Dwork et al. (2012), statistical parity is discussed as worthwhile for achieving group fairness, as it balances the outcomes across all individuals in the group. However, they continue to argue that such parity is insufficient because it is unfair when examined by an individual. The concept of *individual fairness* follows the idea of Fehr & Schmidt (1999), who describe fairness as self-centered inequity aversion. Thereby, each individual evaluates a situation from the self-centered point of view and assesses whether (s)he is treated unequally compared to other individuals. The critical issue is the subjective judgment and perception of a fair allocation which depend on an individual neutral reference outcome based on social and psychological comparisons (Fehr & Schmidt, 1999). For a further discussion of the socio-psychological effects of fairness we refer to Douthitt & Aiello (2001). If several decisions of a similar kind are made over time, the time horizon also matters in assessing fairness.

Time Horizon of Fairness The time dimension shows two different fairness perspectives: Short-term and long-term fairness. While short-term fairness considers only a moment or a short time horizon, long-term fairness refers to a longer observation period. As Shi et al. (2014) state, when particularly scarce resources are allocated, it is difficult to ensure a fair distribution for a short period. A somewhat unfair situation can then be compensated in the following period(s). Hence, long-term fairness is more important for most resource allocation problems. Following Berger-Sabbatel et al. (2005), an allocation is long-term fair if the distribution of resources converges towards $\frac{1}{N}$ for N resources. With the two different perspectives on fairness in mind, this definition of an equal distribution tends towards a group fairness perspective, where resources are balanced. Nevertheless, the individual effects of allocations converge over time, although this has to be quantified differently.

After prescribing different aspects of fairness, a definition from an economic point of view also includes the discussion of indicators for measuring fairness. For this reason, we look at different fairness measures in the following. Jain et al. (1984) present the common *Jain's index* in order to measure the fairness of a resource allocation scheme quantitatively. They define four characteristics that a fairness measure should have: Population size independence, scale and metric independence, boundedness as well as continuity. Showing that *variance*, *coefficient of variation* and *min-max ratio* do not meet these requirements, Jain et al. (1984) define an index that ranges from $\frac{1}{|E|}$ to 1 with $|E|$ corresponding to the number of employees.[1] At this, 1 indicates the best group fairness case because all resources are treated 100% equally. A high value indicating high fairness satisfies the requirement that a measure should be intuitively comprehensible.

In network management, the *Quality of Experience* fairness is used to measure the resource allocation's fairness perceived by the user (Hoßfeld et al., 2016). By this, the individual perspective can be taken into account, as each person evaluates the allocation on a scale. In addition to the mentioned characteristics, Hoßfeld et al. (2016) prescribe deviation symmetry, level independence and validity for multi-applications as needed properties for a general fairness measure. They define the Quality of Experience fairness as $F = 1 - \frac{2\sigma}{H-L}$, where L is the lower and H the upper bound of the used scale and σ corresponds to the standard deviation. As with Jain's index, F is intuitively interpretable and 1 indicates the best case with highest fairness.

Bertsimas et al. (2011) propose two concepts of fairness for resource allocation problems: *max-min fairness* and *proportional fairness*. Proportional fairness can be traced back to Nash (1950), who describes a setting for two players as fair if there is no change that favors one player's utility on a percentage basis more than it discriminates the other's. Based on the Rawlsian principle (Rawls, 1971) and Kalai & Smorodinsky (1975), a solution is defined as optimal according to max-min fairness if the minimum utility level among all players is maximized. Therefore, a distribution is achieved by not allowing for individual's utility increase except at someone else's expense.

The discussion in this section indicates that a universal definition of fairness, the answer to question (i), remains difficult. There are different aspects such as the perspective and the time horizon of fairness as well as different possibilities to objectively measure fairness. If a resource allocation considers both the perspectives of the entire group and the individuals as well as a

[1] For a definition and numerical examples of the three standardized statistical measures and the Jain's index itself, we refer to Jain et al. (1984).

short-term and long-term horizon, the allocation is likely to be fair, which is also expressed by the measures.

3 Fairness in Personnel Scheduling Problems

There are several decision problems related to working in shifts and we present the planning process in the following section. The scheduling and rescheduling problem are examined in more detail in section 3.2, since these affects schedule fairness most. Section 3.3 presents various concepts for incorporating fairness issues in solution approaches.

3.1 Planning Process Related to Shift Work

In personnel planning, resource allocation is the assignment of employees to shifts. Determining specific shifts and their personnel requirements is a problem at the beginning of the personnel scheduling process. Following Ernst et al. (2004b), *demand modeling* and *shift scheduling* take place before the allocation of personnel. As these two decisions are independent of persons, aspects of fairness can hardly be taken into account.

Looking at the personnel management perspective, Warner (1976) distinguishes three related decision problems: *Staffing*, *scheduling* and *rescheduling*. Staffing decisions refer to the decisions on the number of employees including needed qualifications and corresponding individual contractual agreements such as working hours. This kind of decision is usually taken at strategic level. Scheduling decisions relate to the generation of a schedule assigning adequate employees to the defined shifts. Following Bard & Purnomo (2005a), these decisions are made at regular intervals (e.g. weekly or monthly). Decision makers aim at monetary, social or other objectives or even a combination of several objectives. During schedule operations, rescheduling may be needed at short notice if, for example, an unforeseen absence of an assigned employee invalidates the schedule. Since fairness aspects can hardly be taken into account in shift scheduling and staffing decisions, this paper focuses on the planning steps of personnel scheduling and rescheduling which are introduced in the following section.

3.2 The Personnel Scheduling and Rescheduling Problem

To explain the decision problem and corresponding complexity or personnel scheduling, the comprehensible example of a real-world decision problem of nurse scheduling in a ward of a hospital is used. Following Meisels & Schaerf (2003), three shifts per day are common in hospitals (early, late, night). The nurses have several qualifications, different regular working hours per month and sometimes additional individual contractual agreements regarding their workload or suitable shift types. Each nurse may have preferences for work stretches and working times. In addition, for each planning period they may be allowed to request shifts or days on/off. Global constraints in accordance with laws and tariff regulations such as consecutive working days further restrict the decision. Ikegami & Niwa (2003) differentiate between nurse and shift constraints (corresponding to horizontal and vertical scheduling rules). Shift constraints refer to the assignment of all shifts to the needed number of nurses and are therefore likewise known as coverage constraint (e.g.

Vanhoucke & Maenhout, 2009). Nurse demand can be specified exactly or as a minimum number (sometimes also with maximum and optimum values). Specific characteristics of constraints can vary greatly depending on the state, hospital or even on the ward. The same applies to the objectives and the objective function for optimization. Thus, personnel scheduling is not only a feasibility problem, it is especially complex because of the schedules' quality that has to be quantified (Cohn et al., 2006). It is easy to measure monetary objectives, but it is much more challenging to quantify qualitative objectives such as fairness. We discuss several possibilities for modeling fairness objectives in section 4.1.

Personnel rescheduling occurs during schedule operations. It denotes the problem of adapting an existing schedule that has become infeasible due to a disruption in order to meet all constraints, especially the shift constraints. A schedule disruption can be caused by the absence of an already assigned nurse who, for example, is ill or has to replace someone in another ward at short notice. Then the task is the reassignment of one or more shifts to available nurses considering all scheduling rules. In addition to the existing objectives, rescheduling usually aims at minimizing the deviations between the previous (initial) and the new schedule (Mutingi & Mbohwa, 2017).

Personnel scheduling problems are extensively studied in the literature. For in-depth reviews we refer to Ernst et al. (2004a), Ernst et al. (2004b), Van den Bergh et al. (2013) and De Bruecker et al. (2015). Furthermore, we refer to overviews on specific scheduling problems: Cheang et al. (2003) as well as Burke et al. (2004) for nurse scheduling; Erhard et al. (2018) for physicians scheduling; Gans et al. (2003) for scheduling problems in call centers.

Personnel scheduling is proven to be NP-hard (Osogami & Imai, 2000), including consecutiveness makes the problem even harder to solve (Brunner et al., 2013). Despite the enormous complexity of personnel scheduling, a lot of scheduling problems are still solved manually nowadays. The allocation of scarce human resources might be performed more efficient by using a decision support system instead of scheduling by hand. An automation of scheduling can save a lot of time for the decision makers (Burke et al., 2004). According to Warner (1976), essential characteristics of a decision support system for scheduling are coverage, quality, stability, flexibility, fairness and costs.

3.3 Fairness Issues in the Scheduling Process

In recent years, fairness has become often more important than other common optimization objectives like costs, proving that there is a shift towards employee-oriented scheduling. In case of manual scheduling, procedural fairness depends very much on the manager's method and strategy, while automated scheduling using a decision support system can prevent criticism of subjective shift assignment. A relative system efficiency loss might be caused by taking fairness aspects into account when looking at personnel costs or other characteristics (Bertsimas et al., 2012). Fulfillment of all hard constraints is the most important condition for a feasible schedule independent of the objective. To include fairness aspects, De Landtsheer et al. (2018) name an equal distribution of attractiveness or unpopular shifts across all employees. The concept of unpopular shifts is difficult. For example, some employees are more willing to receive extra pay or compensation for night shifts, while others prefer evenings off (Gross et al., 2019). More important, however, is the consideration of individual preferences to maximize employee satisfaction (De Landtsheer et al., 2018). Bard & Purnomo (2007) mention three categories of scheduling methods for considering preferences: cyclic, self- and preference scheduling. In the following, we discuss which of these concepts can be used for fairness consideration.

Cyclic Scheduling From the 1960s to the present, cyclic scheduling has been used to assign nurses to shifts.[2] A cyclical schedule can be described as a repeated schedule in which all employees are assigned to the same consecutive shifts (patterns) that only differ in the day they start. It is often used when a working day is divided into distinct shifts and the demand is stable (Maenhout & Vanhoucke, 2009). Cyclical scheduling allow employees to make plans for their private lives because the shift assignments are well known in advance. It also ensures a fair distribution of workload and different shift types. On the other hand, there is a very limited possibility of taking individual preferences into account because the allocation is predetermined. Therefore, we conclude that cyclic scheduling is not sufficient for considering fairness aspects and a non-cyclic approach would be needed. Non-cyclic scheduling means generating a completely new schedule for each planning period. Thus, it is much more flexible and offers the potential to fulfill (probably changing) individual requests of employees (Bester et al., 2007).

Self-Scheduling As the term indicates, self-scheduling encompasses the independent generation of individual schedules by each employee. The effects reported in Koning (2014) draw: Involving employees in self-scheduling results in higher satisfaction, as employees can create their schedules according to their own preferences by assigning themselves to shifts. There are several solution approaches based on self-scheduling (see for example Bailyn et al. (2007), Rönnberg & Larsson (2010), Ingre et al. (2012), Ásgeirsson (2014)). Bringing together individual schedules to get a schedule that meets all shift constraints can be a difficult task (Bard & Purnomo, 2007) and even as challenging as generating a schedule from scratch. Furthermore, following Bailyn et al. (2007), there may be violations of horizontal scheduling rules because employees do not have the complex rules in mind nor apply them correctly. Such infeasibilities have to be resolved by the management (Ingels & Maenhout, 2017) or by algorithms. The procedure or automation to figure out a feasible schedule after the actual self-scheduling is decisive for the incorporated fairness. When employees are encouraged to develop their schedules on their own, these self-made shift assignments may be regarded as preferences. With this in mind, we consider the preference scheduling approaches discussed in the following to be applicable to self-scheduling based methods as well.

Preference Scheduling According to a definition provided by Bard & Purnomo (2005a), the objective of preference scheduling is to generate high-quality schedules from employee perspective considering shift constraints and cost minimization. Bard & Purnomo (2007) further state that preference scheduling focuses on the fulfillment of individual preferences. With that type of scheduling, preferences regarding working hours and work stretches as well as specific requests for shifts or days on/off are taken into account. Van den Bergh et al. (2013) give additional examples such as preferences towards working together with specific employees or a distinct working location. For scheduling, preferences and requests are usually modeled as soft constraints. Quantifying the

[2]Cyclic scheduling is used for example in Howell (1966), Maier-Rothe & Wolfe (1973), Caprara et al. (1998), Hochbaum & Levin (2006), Bard & Purnomo (2007), Purnomo & Bard (2007), Maenhout & Vanhoucke (2009), Becker et al. (2018) and Breugem et al. (2019).

penalization due to violation of these soft constraints is an important issue in preference scheduling (Stolletz & Brunner, 2012). In 1976, Miller et al. and Warner were the first to publish studies on preference scheduling. The first use penalty costs for violation of schedule pattern characteristics, whereas the latter additionally penalize the deviations from the requested days off. Instead of individual preferences, general preferences are often taken into account during scheduling to improve schedule quality. General preferences refer to any characteristics on an employee schedule that is evaluated in relation to the other's and the corresponding balance.

Following the different aspects of fairness proposed in section 2, we discuss these following the example of nurse scheduling. The outcome of nurse scheduling is a schedule which serves as the most important basis for nurses to assess fairness aspects. Outcome fairness addresses the fair utilization of nurses. Thus, nurse rescheduling must also be taken into account for assessing fairness because the initial schedule does not necessarily reflect actual operations. If all nurses in the ward are treated equally from an objective point of view, the maximum group fairness is achieved. However, it is more challenging to assess individual fairness because each nurse my have her/his own definition and therefore a unitary quantification is hardly possible. Fairness aspects are often considered in one planning period (Erhard et al., 2018) and consequently ensure short-term fairness. In contrast, long-term fairness refers to fair scheduling over time. To achieve this, information from previous periods must be incorporated in the scheduling process.

In summary, with regard to question (ii), we conclude that the identified aspects such as group and individual, short- and long-term fairness are relevant in personnel scheduling. Of the three common practices to consider fairness in personnel scheduling, preference scheduling offers the greatest potential to generate a fair schedule. Accordingly, we focus on solution approaches belonging to this category.

4 Fairness as Optimization Objective in Personnel Scheduling Problems

This section is dedicated to the modeling of fairness objectives in the mathematical optimization according to the aspects mentioned. Scheduling problems concerning working in shifts in organizations that offer services around the clock share similar characteristics regarding their scheduling issues. A common objective in personnel scheduling is cost minimization because personnel costs correspond to a large share of operational costs. In recent years, fairness aspects and abstract objectives like employee satisfaction are becoming increasingly important (Topaloglu & Ozkarahan, 2004). Incorporating fairness objectives creates an efficiency-fairness trade-off – we refer to Bertsimas et al. (2012) and Karsu & Morton (2015) for a detailed discussion. As we focus on fairness aspects in this paper, we do not discuss the economic costs of staff employment. In many real-world scheduling problems there is no clear defined objective for optimization because the quality of schedules is evaluated by the decision maker based on her/his experience and understanding of fairness (Cohn et al., 2006). The schedules differ in their quality sometimes greatly and thus a quantification of an objective function is needed.

As section 3.3 concludes, the focus is on preference scheduling approaches that have been evaluated using real-world or artificial problem instances. In the following, we consider preference scheduling methods from literature modeling a fairness objective for mathematical optimization of personnel scheduling problems. The review is not limited to one industry, although a large number of publications is dedicated to nurse or physicians scheduling. Henceforth, in order to focus on fairness with regard to shift allocation, we omit some areas of scientific literature as briefly described hereafter. We do not take into account approaches on optimizing fairness of costs or wages, course timetabling problems and one-time scheduling problems. In addition, methods based on preferences modeled as hard constraints are excluded. Finally, we do not review solution approaches for the First International Nurse Rostering Competition (Haspeslagh et al., 2014) or for the Second International Nurse Rostering Competition (Ceschia et al., 2015).[3] The following section moves on to describe different modeling approaches of a fairness objective. Afterwards, section 4.2 reviews relevant literature which is presented according to the time horizon considered in the solution approach.

4.1 Common Fairness Indices and Objectives

There are several approaches on how to model an objective function that aims at including fairness aspects. The overall objective is to find a feasible schedule that complies with all hard constraints such as fulfilling the shift constraints at minimal costs and at the same time taking preferences as well as effects on employees into account. Assuming a penalty score p_i for each employee $i \in E$ that indicates, for a given schedule, how high the penalization is for violating soft constraints that affect that employee. The higher the penalty score, the more dissatisfied the employee is with the actual schedule. Accordingly, the most dissatisfied employee is the one with the highest penalty score ($\max_i\, p_i \,\forall\, i \in E$). The penalization can relate to different aspects, such as extra hours or requests for days off. The most common objectives in literature include the following:

[1] *Sum* of all penalty scores which maximizes the overall satisfaction: $min \sum_i p_i$

[2] *Min-max*: Minimize the maximum penalty score in order to increase the quality of the worst individual schedule: $min \max_i\, p_i$

[3] *Range* between the maximum and minimum penalty score: $min\,(\max_i\, p_i - \min_i\, p_i)$

[4] *Mean* ($\bar{p} = \frac{1}{E}\sum_i p_i$) of penalty scores: $min\, \bar{p}$

[5] *Mean deviation* − Sum of the deviations between each penalty score and the mean score: $min \sum_i |\bar{p} - p_i|$

[6] *Standard deviation* ($\sigma = \sqrt{\frac{1}{E-1}\sum_{i=1}^{E}(p_i - \bar{p})^2}$) of penalty scores: $min\, \sigma$

[7] Sum of *squared* penalty scores: $min \sum_i p_i^2$

[8] *Percentage of fulfilled requests* in order to maximize the number of fulfilled requests: $max \sum_i \frac{(1-p_i)|R_i|}{|R_i|}$ with $|R_i|$ corresponding to then number of requests of employee i.

In the following sections, we refer to the specified modeled objectives with [1] to [8].

[3]These instances contain mostly neither general nor individual preferences and no fairness aspects are considered in the overall penalties that are minimized.

First, we take a closer look at solution methods and optimization models, that incorporate fairness aspects focusing on minimization of the total penalties according to objective function [1] with a short-term time horizon – assuming penalization is without any gradations and without taking previous penalties into account. In minimizing the overall amount of penalties, a schedule is generated which violates as few rules and preferences as possible. In the worst case, the same persons will always be affected by violations, because there is no mechanism to ensure that preferences are fulfilled in an equal manner among the employees. If the objective does not aim at a fair distribution of preference fulfillment, the resulting fairness is solver-dependent (Gross et al., 2019). According to the current discussion, such an approach does not adequately reflect a fairness objective (Ouelhadj et al., 2012). Nevertheless, there are some approaches in the literature that use such a method and declare it to consider fairness. With regard to group fairness, penalties refer to different issues such as unpopular shifts (e.g. Bertels & Fahle, 2006), shift pattern (e.g. Millar & Kiragu, 1998; Bard & Purnomo, 2005b) and workload (e.g. Borndörfer et al., 2017; Breugem et al., 2017). Several approaches using an objective function like [1] taking into account individual preferences exist in the literature.[4] Further information on these solution approaches is shown in Table 2 in the appendix.

4.2 Applications of Fairness Objectives in Literature

Table 1 summarizes relevant solution approaches from literature that apply fairness objectives. The approaches are classified into two sets with regard to the time horizon. First, the Table shows the approaches that only consider a short-term horizon for optimization. Second, eight solution approaches are presented that additionally take the long-term dimension into account. In each set the items are in chronological order and the corresponding characteristics regarding group, individual and long-term fairness are presented. In addition, the modeling of the objective function as listed in section 4.1 is classified.[5]

4.2.1 Consideration of Short-Term Fairness

As indicated in section 2, a schedule has the highest group fairness if all employees are treated exactly the same. This equal treatment can relate to different aspects and is therefore dependent on the problem characteristics and the decision maker. The majority of methods aim to distribute the fulfillment of general preferences as workload (L), time-related constraints (T) such as the number of consecutive working days or rest times, unpopular shifts (U) or working on weekends (W) evenly among the employees.

One of the most widespread measures for fairness is maximizing the quality of the worst individual schedule (in other words minimizing the highest individual penalties – [2]). Nishi et al. (2014) use such an objective focusing on the workload. To reduce solution time, they decompose the railway crew rostering problem into a master problem and a subproblem. Results using real-world

[4]Examples are Berrada et al. (1996), Aickelin & Dowsland (2004), Li & Aickelin (2004), Topaloglu & Ozkarahan (2004), Wright et al. (2006), Parr & Thompson (2007), Sabar et al. (2008, 2009), Maenhout & Vanhoucke (2010), Wright & Bretthauer (2010), Burke et al. (2011), Rasmussen et al. (2012), Van Huele & Vanhoucke (2014), Borndörfer et al. (2015), Fügener et al. (2015), Gross et al. (2018) and Xie & Suhl (2015).

[5]At this point it should be noted that this information only refers to the fairness aspects and other objectives such as cost minimization are disregarded. Therefore, the specifications do not necessarily represent the entire objective function.

		Group	Individual	Long	Objective
Short-Term	Trilling et al. (2006)	U	D		[3]
	Brucker et al. (2010)		P, S, W		[2][a]
	Maenhout & Vanhoucke (2011, 2013a, 2013b)	L	S		[1], [5]
	Ouelhadj et al. (2012)	T			[1], [2]
	Smet et al. (2012)	T			[1], [2]
	Stolletz & Brunner (2012)	L, U			[3]
	Martin et al. (2013)	T	S		[1], [2], [3], [5], [7]
	Nishi et al. (2014)	L			[2]
	Komarudin et al. (2014)		S, T		[2], [3], [5], [7]
	Jütte et al. (2017)	U			[5]
	Zhong et al. (2017)	W			[4]
	Doi et al. (2018)	L			[2], [5], [7]
	Lavygina et al. (2019)	T			[1], [6]
Short- & Long-Term	Miller et al. (1976)		P	PEN	[1][b]
	Bard & Purnomo (2005a)		D, L, W	PEN	[1][b]
	Bester et al. (2007)		D, P, (S)	SC	[1][b]
	Alsheddy & Tsang (2011)	T	S	SC	[8][c]
	Ásgeirsson (2014)	L	S	L	[8][c]
	De Landtsheer et al. (2018)	U	S	SC	[1][b]
	Gross et al. (2019)		S	SC	[8][c]
	Wolbeck et al. (2019)	L	S	SC	[3]

[a] This objective is not concretely formulated, but it is aimed at by a construction heuristic.
[b] Since the sum of penalty costs is minimized, in which the previous periods resp. fairness aspects are already taken into account, the modeling is fair according to our definition.
[c] Since the overall fulfillment of requests considers previous periods resp. fairness aspects, the modeling is fair according to our definition.
D = requests for day on/off, L = workload (refers to working hours, number of shifts etc.), P = shift/work pattern, PEN = adjusted penalty costs, S = requests for shift on/off, SC = cumulative score, T = time-related constraints (including rest times, consecutive working days etc.), U = unpopular shifts, W = weekend.

Table 1: Solution Approaches Considering Fairness Aspects in Personnel Scheduling

instances show fair working conditions as well as reduced costs in shorter computational time. Likewise, Smet et al. (2012) use a min-max-formulation in their exact optimization to distribute rest times and other time-related constraints fairly among the physicians of real-world instances. Ouelhadj et al. (2012) use the same modeling of fairness as Smet et al. (2012) for their agent-based heuristic inspired by tabu search and simulated annealing. Both studies compare their results with generated nurse schedules aiming at minimization of the sum of penalties (like [1]). They show that with an explicit consideration of fairness in the objective function much fairer schedules can be achieved in reasonable time without affecting schedule quality. These findings justify the rejection of solution approaches from the overview that pursue only objective [1]. Following the promising results of these two studies, Martin et al. (2013) evaluate further modeling approaches for objective functions. In addition, they consider individual requests for shifts on/off, which is why this approach is discussed in more detail in the next part.

Stolletz & Brunner (2012) schedule physicians aiming at cost minimization combined with fairness aspects. For their exact optimization based on the model from Brunner et al. (2009), they use a weighted objective function and aim at fairness minimizing the ranges between maximum and minimum extra time as well as regarding the number of on-call shifts with a formulation like [3]. The results in Stolletz & Brunner (2012) show that costs increase slightly and solution time increases significantly when fairness aspects are considered. Based on the fairness definition of Fehr & Schmidt (1999), Jütte et al. (2017) present a column generation approach for railway crew scheduling using an objective formulation similar to [5]. In their study, fairness is associated with an even distribution of unpopular shifts determined by their starting time (in order to not disturb the circadian rhythm). Considering the fairness objective besides cost minimization, schedule fairness is significantly increased at roughly the same costs as the minimal costs. Zhong et al. (2017) adopt an objective such as [4], in order to minimize variations in the number of assigned weekend shifts among all nurses. Their two-stage heuristic has already been applied in several hospitals and offers potential to improve working conditions. Comparing three fairness measures, the results of Doi et al. (2018) show that a linear penalty corresponding to an objective like [5] performs best in terms of an equal distribution of working time. Their decomposition-based heuristic is used for real-world airline crew scheduling instances. Focusing on rest times, Lavygina et al. (2019) minimize the standard deviation of penalties ([6]) among physicians using two adapted metaheuristics – simulated annealing and genetic algorithm. Their results indicate that a multi-objective heuristic based on minimizing the total sum of penalties and a fairness driven objective leads to better schedules than considering only one of these as single objective.

When considering group fairness, however, individual preferences are not automatically taken into account. Individual preferences have to be queried in advance, since the preferences with regard to shift types, workload or other aspects are not always the same for all employees (Gross et al., 2019). As discussed in section 3.3, the concept of unpopular shifts is also arguable. Thus, we now discuss approaches aiming at optimizing individual fairness (in some cases combined with group fairness) in the short term. In addition to the aspects to which general preferences refer, individual preferences may relate to days (D) or shifts (S) on/off.

Martin et al. (2013) examine various objective functions distributing penalties to time-related constraints and individual requests for shifts equally among all nurses. Their computational experiments on real-world instances show that meeting all constraints significantly fairer schedules are generated compared to cost optimization. Regarding the objective modeling, the overall mean deviation like [5] outperforms the other, of which the weighted sum of penalties ([1]) performs worst in terms of fairness. To evaluate the schedule and measure fairness, Jain's index is used (Martin et al., 2013).

Besides an equal distribution of unpopular shifts, the approach of Trilling et al. (2006) aims at fulfilling individual nurse requests regarding days off. Fairness is achieved by minimizing the range between the maximum and minimum individual penalty value ([3]). Their integer linear model is slightly better than constraint programming within reasonable solution time reaching good schedule quality. Brucker et al. (2010) use a two-stage heuristic approach for constructing a nurse schedule. The individual schedule with the highest penalties is improved first in order to increase its quality (corresponding to a min-max objective [2]). Doing this, requests for shifts on/off and individual preferences regarding patterns and weekends are considered. Based on their results, Brucker et al. (2010) conclude that the developed heuristic is adaptable to other use cases since hardly any expert knowledge is required to apply it.

Based on the model and the evolutionary algorithm used in Maenhout & Vanhoucke (2011), Maenhout & Vanhoucke use a weighted objective function to distribute the workload equally at nurse rescheduling with minimizing the overall sum of deviations from the mean number of assigned shifts ([5]) in several approaches (Maenhout & Vanhoucke, 2011, 2013a, 2013b). In addition, they take individual shift requests into account. The evolutionary algorithm combined with local search outperforms the best objective function value so far on benchmark instances published in Pato & Moz (2013). Even slightly better schedules for this instances can be achieved with the artificial immune system of Maenhout & Vanhoucke (2013a), which proves its effectiveness. In Maenhout & Vanhoucke (2013b), they use an exact branch-and-price algorithm as well as local search.

Komarudin et al. (2014) investigate the functionality and effectiveness of different objectives for nurse scheduling. In addition to four common objectives (see Table 1), they propose an objective based on lexicographic rules. Experiments on real-world instances reveal that fair schedules are achieved with almost constant schedule quality.

The solution approaches discussed so far have all been limited to short-term fairness. Moreover, most of the published and used solution approaches on employee scheduling only consider the current planning period and do not track fairness over time (Gross et al., 2019). In each approach considered, short-term fairness aspects are taken into account. Since individual indicators are indispensable when taking previous periods and long-term fairness into account, the approaches presented subsequently each include individual preferences.

4.2.2 Consideration of Short- and Long-Term Fairness

The consideration of previous periods leads to increased fairness and ensured feasibility. Following Smet et al. (2017), local and global inconsistencies may occur if previous periods are not considered in scheduling. Local inconsistencies refer, for example, to time-related constraints at the transition between two planning periods and global inconsistencies to individual counters, such as the number of hours worked. Such global counters can also be used for fairness aspects, e.g. if the number of granted requests is counted. Blöchliger (2004) state that previous periods might be considered using an adjusted individual penalty score or changing soft constraints. Further ways for integrating previous schedules and the resulting realization of fairness in scheduling are discussed in the following. Column 'Long' of Table 1 shows the mechanisms used for considering long-term fairness. These mechanism include adjusting the penalty costs (PEN) or using cumulative satisfaction scores (SC).

One of the first solution approaches for nurse scheduling has already taken previous periods into account: Miller et al. (1976) calculate the penalty costs of a pattern based on the employee's individual preferences and history. Using an *aversion index* that indicates whether an employee was previously treated unfairly and had bad shift assignments, the penalties are set correspondingly. Due to the generic functionality based on pattern and the good results of the solution approach, several real-world applications in hospitals are based on it (Miller et al., 1976). Bard & Purnomo (2005a) use an exponential weight for penalty costs that increases with the number of previous preference violations. In this way, they consider previous workload in their column generation approach for nurse scheduling. At the same time, individual requests for days off are included in the penalty calculation. Likewise for nurse scheduling, Bester et al. (2007) present a tabu search algorithm incorporating individual preferences for work patterns and shifts on. The consideration of an accumulated satisfaction score of previous periods extends the solution procedure with regard to long-term fairness. These three approaches mentioned all use an objective function in which the overall sum of penalty costs is minimized as in [1]. Nevertheless, we include these in the overview because they calculate the penalties based on individual conditions and thus affect the fairness. Similarly, all three approaches do not explicitly consider group fairness aspects. However, due to the varying priorities of the employees, group fairness is identified as the most negligible of the four aspects discussed.

The objective of maximizing the number of percentage of granted requests ([8]) is likely to occur when considering individual preferences. We identified the following three publications dealing with such an objective taking into account a cumulative satisfaction score or the workload of previous periods. In their contribution, Alsheddy & Tsang (2011) conclude that group fairness is not more important than individual fairness. Crucial for employee satisfaction and perception of fairness is, in particular, trust in scheduling. In order to increase the perceived fairness, each employee is allowed to score 100 points for her/his preferences and can thus weight the requests for shifts (Alsheddy & Tsang, 2011). Calculating an employee power score, they are able to track preference fulfillment over several periods and thus aim for long-term fairness. The implemented local search algorithm generates schedules for a field workforce which balance employee satisfaction. Based on a partial schedule fulfilling all employee requests if possible, Ásgeirsson (2014) focuses on preference scheduling and state that a black-box algorithm is not appropriate because employees and decision makers want to understand why some preferences are neglected. Requests for days off are modeled as hard constraints and requests for working a shift as soft constraints. Stating that previous periods makes the solution space much smaller and a consideration is necessary for the solution to be feasible, Ásgeirsson (2014) considers previous working times to determine the working hours for the current period of six weeks. The developed heuristic is examined using nurse, call center agent as well as airport ground service employee instances. Gross et al. (2019) use an individual satisfaction indicator for scheduling physicians. Doing this, they take previous schedules and the corresponding fulfillment of preferences into account. Their computational study on three different strategies shows that updating the penalization based on the satisfaction during scheduling reveals the best results. The advantages compared to neglecting previous preference fulfillment become more evident as the number of conflicting preferences increases. Since Gross et al. (2019) state to not balance shift assignments that are not explicitly requested, general preferences and the concept of unpopular shifts are not adopted.

Similar to Alsheddy & Tsang (2011), De Landtsheer et al. (2018) aim to empower employees in order to increase the trust in the scheduling system. Therefore, scheduling needs to be simple, flexible and fair. De Landtsheer et al. (2018) propose a metaheuristic approach combining a greedy algorithm, a local search procedure, tabu search and other metaheuristic inspired concepts to schedule physicians. The shift assignment is based on individual and general preferences as well as on an accumulated score that indicates the individual discomfort. Thus, the algorithm considers fairness both short- and long-term. Also considering both time horizons, Wolbeck et al. (2019)

schedule nursing staff in a care facility. With focus on an equal distribution of workload and extra hours, they use a bi-criteria optimization model. To generalize the model, they use shift pattern that are prepared in preprocessing to reduce the computation time. For most real-world problem instances, all individual requests can be fulfilled with a minimum range between maximum and minimum overtime value (like [3]).

As Table 1 shows, there is a large number of publications that differ in the perspective and time horizon if fairness considered and choose different objective functions. First, we draw a conclusion regarding the two distinct decision problems addressed. One interesting finding is, that only three publications by Maenhout & Vanhoucke (2011, 2013a, 2013b) provide solution approaches for the personnel rescheduling problem. All other approaches focus on the initial generation of a schedule. Taken together, all of the eight indices from section 4.1 are used several times in literature. When minimizing the overall sum of penalty costs, it is important to pay attention to the calculation of penalties. The incorporation of general and individual preferences relates to different characteristics. With regard to group fairness, these can basically be subsumed under workload, since unpopular shifts, time-related requirements and weekend shifts each affect the workload. Accordingly, one objective of fair personnel scheduling should be to distribute the workload evenly among the employees. Thereby, the concrete details depend on the use case. Furthermore, the consideration of individual preferences is indispensable in order to empower employees in the scheduling process and thus increase the positive acceptance of schedules. As the overview reveals, the majority of the solution approaches allow individual requests regarding shifts on/off. This kind of request seems to be most important and therefore a fair fulfillment of such individual preferences should be an essential objective in fair scheduling. Concerning the time horizon, it can be stated that short-term fairness is by definition considered in each fair schedule. Long-term fairness, on the other hand, is by far not taken into account by all approaches, although the positive effects of tracking fairness over time are well known. The most widely used concepts for consideration of previous periods are calculating a cumulative satisfaction or penalty score for each employee as well as adjusting the penalties according to the previous treatment. Thus, unavoidable unfair shift assignments can be compensated in following periods. In order to increase employee satisfaction, long-term fairness is a mandatory objective for optimization. To sum up to question (iii), there are several ways to integrate fairness aspects into personnel scheduling. Most important is the use case specific consideration of group and individual preferences as well as the observation of fairness over a long-term horizon. Ideally, schedules based on different objective functions are generated and further evaluated or the decision maker determines which fits best.

5 Conclusion and Future Research

Considering fairness in personnel scheduling has been of increasing interest in industry as well as research. This paper provides a first comprehensive overview of personnel scheduling approaches that take fairness aspects into account. It presents fairness in the context of economic literature and objectives for mathematical optimization.

We introduced three questions addressing the concept of fairness in the scheduling literature. First, a resource allocation is defined to be fair if group and individual fairness are both considered short- and long-term. Second, preference scheduling offers the greatest potential to generate fair schedules and is superior to cyclic scheduling that, for example, cannot capture changing preferences and requests for shifts on/off. Three, literature handles these aspects differently. Especially quantifying fairness as objective is often modeled very differently in solution approaches. Several solution approaches neglect the relevance of long-term fulfillment of general and individual preferences although it is central for an all-encompassing fairness approach. Literature in the area of fair personnel scheduling has shown to be still a small research area notwithstanding that it provides great potential for improving working conditions and employee satisfaction. Future research could assess the long-term effects of taking information from previous periods into account in the decision making. First approaches into this direction are summarized in this paper. Furthermore, in future research, a more closely examination of fairness in rescheduling needs to be done, since reactive rescheduling of shift assignments probably affects employees even more than initial scheduling.

An issue that was not addressed in this paper are the socio-psychological consequences of shift work and fairness. Companies are investing more and more effort in retaining employees for the long term. Thus, schedules have to be as comfortable as possible for the employees affected. This includes involving and empowering employees in the scheduling process in order to increase acceptance of schedules and satisfaction. Therefore, also a qualitative evaluation in combination with approaches presented is needed. Enhancing optimization models with employees' feedback would be a fruitful area for further research.

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Appendix

		Group	Individual	Long	Objective
Short-Term	Berrada et al. (1996)	P, W	D		[1]
	Millar & Kiragu (1998)	P			[1]
	Aickelin & Dowsland (2004)		P		[1]
	Li & Aickelin (2004)		P		[1]
	Topaloglu & Ozkarahan (2004)		L, W		[1]
	Bard & Purnomo (2005b)	P, U			[1]
	Bertels & Fahle (2006)	T, U			[1]
	Wright et al. (2006)	U	S		[1]
	Parr & Thompson (2007)	T	S		[1]
	Sabar et al. (2008, 2009)		T		[1]
	Maenhout & Vanhoucke (2010)	L	T		[1]
	Wright & Bretthauer (2010)		S, W		[1]
	Burke et al. (2011)	P, W	S		[1]
	Rasmussen et al. (2012)		S		[1]
	Van Huele & Vanhoucke (2014)		L		[1]
	Borndörfer et al. (2015)	U	D		[1]
	Fügener et al. (2015)	U	S		[1]
	Borndörfer et al. (2017)	L, W			[1]
	Breugem et al. (2017)	L, T, W			[1]
	Gross et al. (2018)	L	S		[1]
	Xie & Suhl (2015)	D	D		[1]

D = requests for day on/off, L = workload (refers to working hours, number of shifts etc.), P = shift/work pattern, PEN = adjusted penalty costs, S = requests for shift on/off, SC = cumulative score, T = time-related constraints (including rest times, consecutive working days etc.), U = unpopular shifts, W = weekend.

Table 2: Solution Approaches using an Objective like [1]

Diskussionsbeiträge - Fachbereich Wirtschaftswissenschaft - Freie Universität Berlin
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