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Invited Review

Fatigue, personnel scheduling and operations: Review and research opportunities

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ABSTRACT

Work-related fatigue is a multidimensional phenomenon with significant effects on operational performance. Our work focuses on how the literature of operational research measures and models fatigue and its effects on operational performance, and on how it mitigates those effects. We position the literature of fatigue relative to that of work-rest scheduling, shift scheduling, multitasking, ergonomics, deterioration scheduling, and occupational health and safety. We classify the literature of fatigue across multiple dimensions: the methods by which it is identified and measured; the operational research methodology applied for fatigue prevention or mitigation; the flexibility allowed in work-rest scheduling and in shift scheduling; applications within manufacturing, construction, transportation, hospitals, and services; and the extent to which real data is used and results are implemented. Our work shows that operational research has contributed numerous effective algorithms and heuristic solution procedures to fatigue mitigation. We also identify several important research directions for operational research, to promote its broader and more effective use to identify and mitigate the effects of fatigue on operational performance.

1. Introduction

Our work reviews and synthesizes the literature of *work-related fatigue*, hereafter simply fatigue, with a focus on its effect on operational performance, as studied within operational research. We define fatigue, most simply, as either an objective condition or a subjective feeling of tiredness, caused by a work-related external stimulus. Williamson et al. (2011) give a more general definition, " ... a biological drive for recuperative rest ... fatigue may take several forms including sleepiness as well as mental, physical and/or muscular fatigue depending on the nature of its cause". Fatigue is multidimensional and complex (Gawron, French, & Funke, 2001). It includes every loss caused by a physical or mental effort within the workplace, and thus includes both physiological and psychological fatigue. Physiological fatigue, which includes muscle fatigue and nervous system fatigue, is induced by doing a task with a predetermined force for a certain time. Psychological fatigue includes the boredom and tiredness a worker feels while performing a task. The measurement of fatigue is complicated not only by its heterogeneous nature, but also because it is a subjective reaction to external stimuli rather than an observable stimulus itself.

Fatigue is a pervasive and significant problem for workers in various industries and the organizations that employ them. Fatigued individuals are a strain on themselves and their families, their employers and society due to decreased productivity, increased risk of negative safety outcomes, and increased illness, especially cancer and heart disease. The literature reports significant effects of fatigue on job performance, as measured by diminished quality of work, more frequent errors and adverse events, reduced client satisfaction (Caruso, 2015; Dall'Ora, Ball, Recio-Saucedo, & Griffiths, 2016) and productivity (Rosekind et al., 2010), and increased safety problems (Lombardi, Folkard, Willetts, & Smith, 2010). Declining performance (including quality, productivity and safety) as a result of fatigue is observed in those on shift work, night shift, rotating shifts, overtime work, and in those working long hours on the same task (Barker & Nussbaum, 2011; Olds & Clarke, 2010). The economic costs attributable to fatigue are also considerable. The National Safety Council (NSC, 2018) reports that a typical employer with 1000 employees incurs a cost of more than $1 million each year due to fatigue: $272,000 due to absenteeism and $776,000 due to working while fatigued. Rosekind et al. (2010) find that fatigue-related lost productivity costs employers

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between $1,293 and $3,156 per employee annually. NSC (2019) estimates that fatigue costs U.S. employers $136 billion a year in health-related lost productivity globally. For all the above reasons, it is important for companies to understand the causes and effects of fatigue, as well as effective ways to mitigate it.

As discussed above, fatigue arises in many different ways and has significant effects on operational performance. Our work focuses on how the literature of operational research measures and models fatigue and its effects on operational performance, and on how it mitigates those effects. Positioning the fatigue literature is complex, because of several closely related topics. We discuss the relation between the literature of fatigue and that of work-rest scheduling, shift scheduling, multitasking, ergonomics, deterioration scheduling, and occupational health and safety. We describe our survey methodology. Next, we classify the literature of fatigue across multiple dimensions: the methods by which it is identified and measured; the operational research methodology applied for fatigue prevention or mitigation; the flexibility allowed in work-rest scheduling and in shift scheduling; applications within manufacturing, construction, transportation, hospitals, and services; and the extent to which real data is used and results are implemented. Our use of a broad variety of applications enables us to study diverse causes of fatigue. For example, lack of temperature control is a major cause of fatigue in construction, whereas monotony is a larger issue in transportation. We demonstrate that operational research has contributed numerous effective algorithms and heuristic solution procedures to fatigue mitigation. We also identify several important research directions for operational research, to promote its broader and more effective use to mitigate the effects of fatigue on operational performance. Our work facilitates access to the extensive literature of fatigue, and identifies ways for operational research to mitigate its effects more effectively.

This paper is organized as follows. Section 2 describes our methodology and positions the literature of fatigue within the literatures of various related topics. Section 3 discusses fatigue measurement and prediction. Section 4 discusses work-rest scheduling and shift work scheduling, how they impact fatigue, and how operational research can be used to mitigate it within those contexts. Section 5 discusses the main operational applications where fatigue is an issue, and explains how it arises differently and is addressed differently by operational research within them. Section 6 examines different ways in which data is sourced and used, and results are implemented. Section 7 documents opportunities for future research. Section 8 concludes the paper with a summary of our work and some insights for operational improvement.

2. Survey methodology

We describe our process for finding sources for our review that follows in Sections 3–6. For current relevance, we restrict the time horizon to the period 2009–2019, with the caveat that a few early seminal works are also included. We perform literature search in the databases Web of Science: Science Citation Index Expanded (from 1998) and Social Sciences Citation Index (from 2008), since they include most influential academic sources. We also perform additional focused search in Google Scholar.

To conduct a systematic literature review (Denyer & Tranfield, 2006), identifying and analysing all available evidence related to fatigue, personnel scheduling and operations, we search 75 combinations of keywords, as shown in Table 1, which define components of fatigue (Category A), application areas (Category B), and operational models related to fatigue (Category C). The keywords within Category A come from the literature of ergonomics, which studies the interaction between the performance of systems and human factors, and within this interaction fatigue is a well studied concept. The keywords within Category B identify high value application areas where fatigue is a significant issue. They present different sources of fatigue and different challenges in its mitigation. Further discussion appears in Section 5. The keywords in category C represent established operational research models relevant to fatigue. These keywords enable us now to position the literature of fatigue relative to other topics within operations listed in Table 1. In doing so, we mention some related surveys.

First, and most closely related to fatigue, is the literature of work-rest scheduling associated with personnel scheduling. Ernst, Jiang, Krishnamoorthy, Owens, and Sier (2004) provide a bibliography of about 700 references for personnel scheduling, with a focus on algorithms for generating schedules rather than explicitly on fatigue. Van Den Bergh, Belien, De Bruecker, Demeluemeester, and De Boeck (2013), based on a literature review, present the personnel scheduling process within several modules: shift definition, performance measures, solution methods, and application area, also without discussing the impact of fatigue. Nonetheless, these two articles provide valuable background about personnel scheduling, which is needed to understand the impact and mitigation of fatigue. Lodree, Geiger, and Jiang (2009) review the impact of incorporating human characteristics into classical scheduling theory. Their framework studies fatigue by considering time-dependent processing times, and recovery by considering the scheduling of one or more breaks within the scheduling horizon. The first work-rest model, which determines the optimal length and placement of one break over a finite time horizon for an employee with a decreasing work rate, is due to Eilon (1964). The amount of research with different objectives, for example, optimizing the number of workers assigned to every shift and work-rest policy (Aykin, 2000), maximizing labor productivity (Bechtold, Janaro, & Sumners, 1984) and optimizing the number of rest breaks (Li, Xu, & Fu, 2019b), is expanding rapidly. Some work-rest scheduling models allow flexibility as to the exact timing of rest breaks (Zhan & Ward, 2019). This is especially important when the intensity of work varies during the day, for example in service systems with randomly varying demand (Brunner & Bard, 2013). Models within the literature of work-rest scheduling take into account recovery rate, since a slower recovery rate necessitates more recovery time before work can resume. Estimation of recovery time is a growing subtopic here (Chan, Yi, Wong, Yam, & Chan, 2012; Ma, Zhang, Wu, & Zhang, 2015).

Second, the more general literature of shift scheduling (or, job rotation-, personnel-, workforce-, employee-, staff-, or labor-scheduling) has been influential in both theory and practice, for example for hospitals (Warner & Prawda, 1972) and for the airline industry (Barnhart, Cohn, Johnson, Klabjan, & Nemhauser, 2003). Shift scheduling involves the allocation of employees within a workforce over a given period of time (usually weeks or months) to shifts characterized by minimum staff level requirements (Lodree et al., 2009). In both hospitals (Roets & Christiaens, 2019) and transportation (Geiger-Brown et al., 2012), fatigue is a significant concern. Some shift scheduling models consider the development of optimal shifts without consideration of fatigue. However, some of those shifts are more likely to result in increased fatigue than others. Improved scheduling of shiftwork has been recognized as an effective general countermeasure against fatigue risk. This has been observed particularly in nurse scheduling (Barker & Nussbaum, 2011). Otto and Battaia (2019) provide an overview of optimization approaches to assembly line balancing and job rotation scheduling that consider fatigue. The shift scheduling problem becomes more complex when each employee's work assignment must be assigned for an entire week, since in addition to the daily shifts, the days off and tour scheduling problems must be defined (Gentzler, Khalil, & Sivazlian, 1977; Veldhoven, Post, Veen, & Curtois, 2016). As a result, there has evolved a literature within per-

Table 1
Categories of words utilized for the literature search.

Category A	Category B	Category C
fatigue, boredom, tired, break, rest	manufacturing, construction, transportation, hospitals, services	work-rest scheduling, shift scheduling, job rotation scheduling, personnel scheduling, workforce scheduling, manpower scheduling, employee scheduling, staff scheduling, labor scheduling, multitasking

Note. Our search process combines keywords in Categories A with keywords in either of Categories B and C resulting in $(5 \times 5) + (5 \times 10) = 75$ search combinations.

sonnel scheduling that combines the design of efficient shift schedules with sensitivity to fatigue.

Third, the multitasking literature touches on the topic of fatigue in various ways. Multitasking is defined as switching between unfinished tasks (Adler & Benbunan-Fich, 2013). A major cause of psychological fatigue is boredom, for example from a lack of variety in work tasks (Deery, Iverson, & Walsh, 2002). Multitasking may increase creativity, thereby alleviating boredom (Lu, Akinola, & Mason, 2017). Mathematical models of general multitasking situations are developed by Hall, Leung, and Li (2015). However, the direct application of models of this type to avoid or mitigate fatigue has not been seen, and requires substantial empirical support. Additional comments on this topic appear in Section 7.

Fourth, the ergonomics literature, which provides useful structure to our literature search process (see Table 1), studies the interaction between the performance of systems and human factors, and within this interaction fatigue is a well studied concept. Bendak and Rashid (2020) review the literature of fatigue in aviation, with a focus on causes, consequences, measurement, and countermeasures to mitigate fatigue. Their work has a strong focus on fatigue but makes limited use of operational research.

Several other topics fall less directly within our scope. Works on material fatigue and breakages fall outside our scope. The model of Lodree and Geiger (2010) for machines that experience performance degradation over time can be motivated by workers who experience fatigue, but their results are difficult to translate prescriptively into that context. Similarly, deterioration scheduling considers a class of scheduling problems where the processing time of a job grows with its start time and sequence. The deteriorating job scheduling problem is introduced by Browne and Yechiali (1990), who consider a single machine scheduling problem with deteriorating jobs. Since then, machine scheduling problems with deteriorating jobs have received more attention (Joo & Kim, 2013; Sun & Geng, 2019); however, this literature requires more empirical support than it presently enjoys to enable it to mitigate fatigue in practical situations.

The literature of occupational health and safety defines fatigue as both a decrement in performance and a subjective feeling (Mountstephen & Sharpe, 1997), which is consistent with our definition in Section 1. Gifkins, Johnston, Loudoun, and Troth (0000) provide a review of the literature of fatigue and recovery among shift working nurses. They identify factors, for example age, family responsibilities, and lack of exercise, that particularly impede recovery from fatigue. However, the main focus of the occupational health literature is on preventing health issues arising or alleviating them after they have occurred, with a focus that is more on health outcomes than on operational performance. Moreover, it is rare for the occupational health care community to make decisions about operational design or improvement. Further, most of the proposed solutions are outside the scope of operational research. Given our focus on the effect of fatigue specifically on operational performance, and how operational research can be used to mitigate that effect, these topics are less closely related to our work than those discussed above.

We describe our methodology for selection and classification of the published work, by first defining some limitations on our scope. For inclusion within our scope, the main research topic of a work needs to be directly attributable to fatigue, not merely to human factors in general. Our work supports a manager or senior manager of an operational process; this also defines a limit on our interest in the connection between fatigue and safety, for example in transportation where fatigue is a factor. Also, works are excluded if they do not discuss one or more issues related to our main focus, which is improving operational performance whenever fatigue is a factor. These scope restrictions enable us to establish a coherent body of content.

We perform a supplementary search in Google Scholar databases, using the whole text of articles. For this supplementary search, we combine the five application areas in category B which had the most hits in our main search with the keywords in category A in Table 1. We also perform a detailed snowball search for works located with Web of Science and Google Scholar. As a consequence, about 1,460,000 articles include one or more of the above keywords in their title, abstracts, author-supplied keywords, and/or full-text. To achieve the highest level of relevance, only peer-reviewed articles written in English and published in international journals are selected; master's and doctoral dissertations, textbooks, working papers and notes are excluded from this review. This process, applied to the Google Scholar and Web of Science databases, excludes almost 1,300,000 articles. Then, a more detailed examination of the titles and abstracts identifies articles that are not primarily about fatigue as it affects an operational process. This process leaves almost 2200 articles. Finally, we apply a detailed screening of those 2200 papers, where the content of each article is reviewed to ensure that it falls within our defined scope, resulting in a set of 300 papers. After removing duplicates, we complete our search with 118 papers. Fig. 1 shows the evolution of these publications over time, with an overall increasing trend.

3. Fatigue measurement and prediction

Fatigue measurement and prediction are performed using a variety of methods and tools which can be classified into two categories, objective and subjective methods (Voelker, Kirchner, & Bock, 2016). Much as fatigue occurs in various ways depending upon the work environment, fatigue measurement methods also use diverse models and different dimensions. Correct evaluation of fatigue is helpful not only in providing reasonable work-rest regimens and shift design, but also in reducing injuries for workers and minimising the related costs. This section discusses several of the more recent and successful methods, identifying both fatigue estimation measures and models. Table 2 summarizes the methods used to measure fatigue.

3.1. Objective methods of assessing fatigue

The objective methods of assessing fatigue can be classified as online operator monitoring, quantification of accumulated fatigue, and performance-based monitoring.

3.1.1. Online operator monitoring

Online operator monitoring technology observes the operator himself/herself, rather than his/her performance. It incorporates

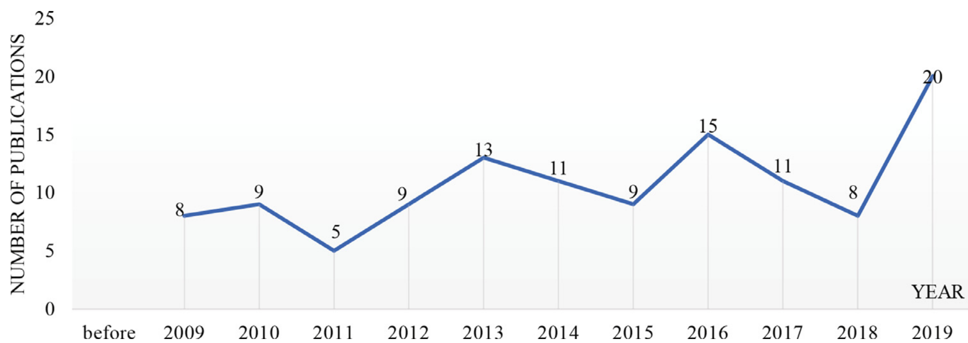

Fig. 1. Number of publications per year.

Table 2
Classification based on fatigue measurement.

Methods		Reference
	Online operator monitoring	Jap et al. (2009), Zhao et al. (2012), Fu et al. (2016), Battini et al. (2016), Yi et al. (2016), Aryal et al. (2017), Chowdhury and Nimbarte (2017), Li et al. (2019a)
Objective methods of assessing fatigue	Quantification of accumulated fatigue	El Ahrache and Imbeau (2009), Ma et al. (2009), Jaber and Neumann (2010), Wang and Ke (2013), Jaber et al. (2013), Wang and Liu (2014), Perez et al. (2014), Zhang et al. (2014), Dode et al. (2016), Seo et al. (2016), Ferjani et al. (2017), Sobhani et al. (2017), Glock et al. (2019), Yu et al. (2019b)
	Performance-based monitoring	Kc and Terwiesch (2009), Ryvkin (2011), Wang et al. (2014), Dong et al. (2015), Delasay et al. (2016), Miklos-Thal and Ullrich (2016), Delasay et al. (2019)
Subjective measures of fatigue		Geiger-Brown et al. (2012), Fang et al. (2015), Zhang et al. (2015), Yildi et al. (2017), Bowden and Ragsdale (2018), Steege et al. (2018), Chang et al. (2019)

common fatigue monitoring apparati capable of providing meaningful measures of performance and alertness in real time. Various methods are used for real-time estimation of neuromuscular fatigue. The fatigue evaluation method of Garg, Chaffin, and Herrin (1978) is based on the energy expenditure assessment of standard operations execution, as a function of oxygen consumption. Its simplicity has allowed its wide use in many applications, such as manufacturing, hospitals, and services. Battini, Delorme, Dolgui, Persona, and Sgarbossa (2016) apply an alternative method developed by Garg et al. (1978) using analytical ergonomic measurement systems based on oxygen or metabolic consumption, where each movement requires a specific energy expenditure. The proposed predetermined motion energy system reduces the time spent to calculate ergonomics measures and simplifies the ergonomics assessment of each assembly task. Yi, Chan, Wang, and Wang (2016) develop an early warning system for construction workers. This system involves collecting timely energy expenditure, heart rate and oxygen consumption data. The proposed system can proactively prevent the onset of construction work-related fatigue and enhance performance. An electroencephalogram (EEG) signal is one of the most predictive and reliable indicators, since it directly provides abundant information about human cognitive states. Jap, Lal, Fischer, and Bekiaris (2009) use the EEG signal to show changes in brain wave activity with fatigue during driving. Yang, Lin, and Bhattacharya (2010) use EEG and electrocardiography (ECG) measures to construct a probabilistic driver fatigue detection model from dynamic Bayesian networks, to enhance the reliability of fatigue detection. Zhao, Zhao, Liu, and Zheng (2012) measure psychosocial fatigue in drivers, also using EEG and ECG data. Their simulation-based experiments indicate that driver fatigue is accurately estimated. A dynamic fatigue detection model, which integrates observations from various physiological sources such as EEG, along with context information, to estimate driver fatigue, is proposed by Fu, Wang, and Zhao (2016). Surface electromyography (SEMG) is a preferred method of many ergonomists. For example, Chowdhury and Nimbarte (2017) find that a reduction in stationarity is observed with the development of fatigue. Thus, the stationarity of SEMG signals can be used to quantify muscle fatigue under static and dynamic task conditions.

Real-time fatigue monitoring of construction workers can enhance construction site safety and help to prevent accidents. Aryal, Ghahramani, and Becerik (2017) develop a sensing system, consisting of infrared sensors attached to a construction safety helmet, the collection of skin temperature from the face, and Heart Rate (HR) and brainwave signals, for real time fatigue monitoring in construction workers. Results show that monitoring thermoregulation provides more valuable information than monitoring HR for fatigue assessment. Li, Wang, Umer, and Fu (2019a) use wearable eye-tracking technology to evaluate the impact of psychosocial fatigue on construction operators' ability for hazard detection and awareness. Their results demonstrate its effectiveness.

3.1.2. *Quantification of accumulated fatigue*

We discuss works that quantify fatigue. El Ahrache and Imbeau (2009) point out that existing works focus mainly on the estimation of the Maximum Endurance Time (MET) or maximum fatigue for muscular exertion. As shown in Table 3, for example, Perez, Looze, Bosch, and Neumann (2014) use discrete event simulation (DES), biomechanical analysis, and static fatigue models to estimate fatigue rate. This allows system designers to understand the ergonomic impacts of proposed alternatives in system design. Integrating both human fatigue-recovery patterns and learning into DES models of a production system, Dode, Greig, Zolfaghari, and Neumann (2016) use the general MET model for operator fatigue prediction. Results show that this approach allows management of fatigue in early design stages where changes are easy and inexpensive. These MET models are the most frequently used when the worker performs one repetitive task with the same muscular force.

When workers perform different types of tasks, various fatigue models are proposed (see Table 3). Ma, Chablat, Bennis, and Zhang (2009) propose a muscle fatigue model which reflects the influence of external load, workload history, and individual differences.

Table 3
Fatigue models.

Reference	Model	Parameters
Perez et al. (2014)	$fF_i = \frac{t_i}{MET_i}$	fF_i is the fraction of fatigue contribution per $task_i$; MET_i is the maximum endurance time for $task_i$.
Dode et al. (2016)	$MET = (7.96)e^{-4.16(\%MVC/100)}$	MVC is the maximum voluntary contraction of a muscle to perform any task.
Ma et al. (2009)	$\frac{dU(t)}{dt} = \frac{MVC}{F_{cem}(t)}\frac{F_{load}(t)}{F_{cem}(t)}$	$U(t)$ is the fatigue index; MVC describes the maximum force generation capacity of an individual muscle; $F_{cem}(t)$ describes the current capacity of a muscle; $F_{load}(t)$ represents external load.
Jaber and Neumann (2010)	$L^i_{\max} = MLC * f_i * MET_i$	$L^i_{\max}$ is the maximum fatigue index for task i; MLC is maximum load capability; f_i is an individual's maximum capability; MET models are described in El Ahrache and Imbeau (2009).
Jaber et al. (2013)	$F(t) = 1 - e^{\lambda t}$	$F(t)$ is the fatigue accumulated by time t; λ is the fatigue parameter.
Wang and Ke (2013)	$x_{i,j} = x_{i,0}e^{T\sum_{l=1}^{j} k_{i,l}}$	$x_{i,j}$ represents the ith person's fatigue state at the jth interval of length T; $k_{i,j}$ is used to represent the fatigue coefficient.
Sobhani et al. (2017)	$F_{jt} = 1 - e^{\theta_j t}$	F_{jt} is the percentage of maximum fatigue developed by the "injured" operator; θ_j is the workload level at the workplace.
Ferjani et al. (2017)	$G_j(\theta) = 1 - e^{d_j\theta}$	$G_j(\theta)$ is the level of worker fatigue when he/she is assigned to machine j for a duration θ; d_j is a penalty coefficient.
Glock et al. (2019)	$F_S(t_a) = 1 - e^{-\theta_a t_a}$; $F_T(t_w) = \beta F_S(t_w)$	$F_S(t_a)$ is the fatigue accumulated by time t_a; θ_a is a fatigue growth parameter when a worker completes an action a during time t_a; $F_T(t_w)$ is the dynamic (real) fatigue.

Their model can be easily applied to real-time virtual work simulation and evaluation. Zhang, Li, Zhang, Ma, and Chen (2014), Seo, Lee, and Seo (2016) and Yu, Li, Yang, Kong, and Luo (2019b) adapt the theoretical models of Ma et al. (2009) for predicting muscular strength and maximum endurance time. The results of the muscular strength prediction show that the predictability of the muscular strength model is acceptable. For air traffic controllers, Wang and Ke (2013) establish an exponential model to describe fatigue levels. Their model shows that fatigue builds up faster when the employee is in a higher fatigued state under the same workload. To track fatigue variation at highly fatigued states, Wang and Liu (2014) propose a fatigue dynamics model where the rate of fatigue development changes when the fatigue state is higher than some prespecified level. The proposed model monitors a series of individual physiological features that objectively reflect fatigue.

Jaber and Neumann (2010) assume that fatigue increases linearly over time, at a rate that is modified when new data becomes available. Their model accounts for operator fatigue in the design of dual-resource constrained systems. The linearity assumption can be questioned. Subsequently, Jaber, Givi, and Neumann (2013) focus on muscular fatigue to sustain a specific posture or force level required to perform a task. They assume that fatigue increases exponentially over time under the lever of the muscle's Maximum Voluntary Contraction (MVC). In accordance with Jaber et al. (2013), as shown in Table 3, Sobhani, Wahab, and Neumann (2017), Ferjani, Ammar, Pierreval, and Elkosantini (2017) and Glock, Grosse, Kim, Neumann, and Sobhani (2019) also use an exponential function to model work-related excessive fatigue. However, Sobhani et al. (2017) allow the workload variation to modify the excessive fatigue level of the operator. Ferjani et al. (2017) assume that fatigue comes from the work performed on machines, and that the time when the worker is not assigned does not significantly affect the level of fatigue, so that waiting neither increases nor decreases fatigue. Glock et al. (2019) argue that a model which estimates total static fatigue cannot completely mimic the dynamic activities involved in the packaging process. Hence, the dynamic real fatigue generated by the packaging process activities is calculated by multiplying the estimated total static fatigue level by a coefficient that can be approximated empirically.

3.1.3. Performance-based monitoring

Performance may be measured on primary features related to an operator's main function such as tracking performance and vehicle speed while driving, or alternatively measured from secondary features such as overwork, service time and service slowdown. There is growing evidence that fatigue because of overwork has detrimental effects on future productivity and decision-making ability (Kc & Terwiesch, 2009; Miklos-Thal & Ullrich, 2016; Ryvkin, 2011). Kc and Terwiesch (2009) model overwork to evaluate the nature and severity of fatigue. High workload results in significant fatigue. Ryvkin (2011) discusses fatigue that accumulates across stages, in a way that captures a key tradeoff of overwork: the expenditure of large effort increases an agent's productivity in the short run. Miklos-Thal and Ullrich (2016) incorporate fatigue by assuming that an agent's payoff from winning is decreasing in effort during the early stages of the Euro Cup. Analogously with Kc and Terwiesch (2009), Delasay, Ingolfsson, and Kolfal (2016) model overwork using a state variable that is incremented with each service completion in a high-load period and decremented at a rate that is proportional to the number of idle servers during low-load periods. Service times that increase with each subsequent service completion demonstrate fatigue. Wang, Jouini, and Benjaafar (2014) consider service times that exhibit both increasing and decreasing trends at different times, for example initial learning by servers, followed by eventual fatigue. In Delasay, Ingolfsson, Kolfal, and Schultz (2019), a state variable is used to count the number of customers served during the current busy period, as a measure of fatigue. They show that average service time increases when servers become fatigued. Under high congestion levels, agents work under pressure and without proper rest, which may eventually lead to deterioration in productivity. Dong, Feldman, and Yom-Tov (2015) use an Erlang-A model to account for slowdown effects caused by fatigue of agents. The above methods efficiently compute standard system performance measures, and identify workers at high risk of fatigue.

3.2. Subjective measures of fatigue

The objective methods of fatigue discussed in Section 3.1 have scientific advantages in reliability and validity. Nevertheless, measuring and assessing workers' psychological fatigue still relies on their subjective assessments, such as fatigue assessment scales for workers. Several studies apply various subjective assessment scales to evaluate the level of psychological fatigue of workers in hospitals, transportation and construction. Two well validated subjective fatigue/sleepiness scales are the Occupational Fatigue Exhaustion Recovery (OFER) scale and the Samn-Perelli fatigue scale. The OFER scale consists of 15 items, with responses given using a scale from strongly disagree to strongly agree, based on experiences of fatigue and stress. This scale has been validated by a study of nurses, where it delivers high test-retest reliability (Geiger-Brown et al., 2012). Using the OFER scale, Steege, Pasupathy, and Drake

Table 4
Classification by research methodology.

Research Methodology	Reference
Mathematical programming	Brunner et al. (2009), Brucker et al. (2010), Lodree and Geiger (2010), Jaber and Neumann (2010), Kok et al. (2010), Ozturkoglu and Bulfin (2012), Stolletz and Brunner (2012), Brunner and Bard (2013), Gunawan and Lau (2013), Jaber et al. (2013), Wang and Ke (2013), Wang and Liu (2014), Todovic et al. (2015), Bowers et al. (2016), Cuevas et al. (2016), Rahimian et al. (2017), Zhu et al. (2017), Baucells and Zhao (2019), Finco et al. (2019), Glock et al. (2019), Hong et al. (2019), Jamshidi (2019), Shuib and Kamarudin (2019), Zhao et al. (2019)
Heuristic	Brunner et al. (2009), Hsie et al. (2009), Ozturkoglu and Bulfin (2012), Stolletz and Brunner (2012), Burke et al. (2013), Gunawan and Lau (2013), Rancourt et al. (2013), Bowers et al. (2016), Cuevas et al. (2016), Veldhoven et al. (2016), Rahimian et al. (2017), Cheng et al. (2018), Hong et al. (2019), Zhao et al. (2019)
Queueing	Dietz (2011), Sun and Whitt (2018), Zhan and Ward (2019)
Empirical	El Ahrache and Imbeau (2009), Barker and Nussbaum (2011), Chan et al. (2012), Geiger-Brown et al. (2012), Matthews et al. (2012), Roach et al. (2012), Yi and Chan (2013), Chen and Xie (2014a), Chen and Xie (2014b), Han et al. (2014), Pisarski and Barbour (2014), Perez et al. (2014), Ma et al. (2015), Martin (2015), Ye and Pan (2015), Dode et al. (2016), Li et al. (2016), Seo et al. (2016), Pasquale et al. (2017), Baucells and Zhao (2019), Chavaillaz et al. (2019), Yu et al. (2019a), Roets and Christiaens (2019)

Table 5
Classification by work-rest flexibility.

Level of Flexibility	Reference
Flexible number of breaks only	Lodree and Geiger (2010), Ozturkoglu and Bulfin (2012), Rancourt et al. (2013), Yi and Chan (2013), Hallbeck et al. (2017), Zhu et al. (2017), Baucells and Zhao (2019), Chavaillaz et al. (2019), Zhan and Ward (2019), Zhao et al. (2019)
Flexible break length only	El Ahrache and Imbeau (2009), Chan et al. (2012), Roach et al. (2012), Perez et al. (2014), Ma et al. (2015), Ye and Pan (2015), Calzavara et al. (2019)
Flexible break length and number	Hsie et al. (2009), Jaber and Neumann (2010), Kok et al. (2010), Roach et al. (2012), Jaber et al. (2013), Rancourt et al. (2013), Yi and Chan (2013), Chen and Xie (2014a), Chen and Xie (2014b), Ma et al. (2015), Pasquale et al. (2017), Glock et al. (2019), Zhan and Ward (2019), Jamshidi (2019), Baucells and Zhao (2019)

(2018) assess the acute fatigue, chronic fatigue, and intershift recovery, of nurses. Their results suggest the need to consider multiple interacting variables or sources of fatigue together. Chang, Yang, and Hsu (2019) use the Samn–Perelli fatigue scale to measure air traffic controllers' fatigue levels. The Karolinska Sleepiness Scale (KSS) measures the subjective level of sleepiness at a particular time during the day by simply asking a driver to rate their sleepiness on a 9-point Likert scale. Yildi, Gzara, and Elhedhli (2017) measure the accumulated fatigue experienced by airline crew members using the KSS. Bowden and Ragsdale (2018) also propose a fatigue-aware model for determining the optimal schedule for a driver while maintaining an acceptable level of alertness, in accordance with the KSS. The Fatigue Assessment Scale for Construction Workers (FASC), developed by Fang, Jiang, Zhang, and Wang (2015) and Zhang et al. (2015), models critical fatigue symptoms among construction workers. Despite their wide application, subjective assessment methods have inherent flaws, such as giving different results when a person's feelings and thoughts about mental fatigue are measured.

4. Personnel scheduling and fatigue

Within personnel scheduling, two research areas support the study of fatigue: (i) work-rest (or rest break) scheduling, and (ii) shift scheduling. Work-rest scheduling is concerned with determining the number, placement, and duration of rest times during a work period. The use of work-rest scheduling to alleviate fatigue is discussed in Sections 4.1 and 4.2. The use of shift scheduling, as defined above in Section 2, to alleviate fatigue, is discussed in Sections 4.3 and 4.4. Our discussion explains the interface between personnel scheduling and fatigue research, and shows how scheduling decisions affect fatigue. Table 4 summarizes different personnel scheduling methodologies applied to the study of fatigue. The operational research methods used in the literature reviewed include mathematical programming, queueing, and heuristics. Empirical studies are also used to provide solutions. For work-rest scheduling, the balance between working time and rest breaks is a key to achieving overall optimality. Table 5 shows different levels of flexibility for the implementation of rest breaks. Allowing the worker to choose the break length or timing contributes flexibility that is useful when workload varies. For shift scheduling problems, organizations use different shift start times, shift lengths, and shift timing to provide flexibility. Rest allowance models are described in Table 6. Table 7 lists alternative types of flexibility for shift decisions, which are classified as fixed and definable.

4.1. Operational research in work-rest scheduling

In work-rest scheduling, workers regularly use rest breaks with fixed lengths during work shifts which allows them to recover or mitigate some of the negative effects of fatigue. The rate-modifying activity (RMA), an activity that changes the production rate of a worker and no work is processed during the duration of this activity, is applicable to workers who experience performance degradation over time due to fatigue and require maintenance to sustain an acceptable production rate. Lodree and Geiger (2010) study a sequence-independent, single processor makespan problem with position-dependent processing times, and prove that under certain conditions, the optimal policy is to schedule the RMA in the middle of the task sequence. Ozturkoglu and Bulfin (2012) define an RMA as a resting period of workers in warehousing systems. An optimization model and a polynomial time heuristic for minimizing makespan are developed to decide the sequence in which jobs should be scheduled, and when to use rest breaks. Motivated by the behavioral phenomena that occur while human operators are carrying out tasks, Zhu, Zheng, and Chu (2017) study multitasking scheduling problems with an RMA. They propose scheduling models and algorithms to minimize: (a) makespan, (b) total completion time, (c) maximum lateness, and (d) due-date assignment related cost, by determining when to schedule the rate modifying activity and the optimal task sequence.

Several studies focus on standard and micro breaks as a means to alleviate fatigue with prolonged or repeated office-related tasks. Following the study of Ozturkoglu and Bulfin (2012), Zhao et al. (2019) present a work-rest scheduling model and a genetic algorithm (GA)-based mechanism to minimize picking time and picking error rate. When error rates increase and picking time increases, they introduce a fixed-length rest break. Given the orig-

Table 6
Rest allowance models.

Reference	Model	Parameters
El Ahrache and Imbeau (2009)	$RA = 100(1 - f \times d)/(f \times d)$	RA is rest allowance; f is the acceptable frequency of exertions; d is the average duration of a single exertion.
Chan et al. (2012)	$R = 0.001T^2 + 3.174T + 43.764$	R is the rate of recovery (%); T is the recovery time in minutes.
Jaber et al. (2013)	$R(\tau_i) = F(t)e^{-\mu\tau_i}$	$F(t)$ is the fatigue accumulated by time t; $R(\tau_i)$ is the residual fatigue after a rest break of length $\tau_i \geq 0$; μ is the recovery parameter.
Dode et al. (2016); Perez et al. (2014)	$RA = 3 \times MET^{-1.52}$	MET is the maximum endurance time (in seconds) for a task.
Ma et al. (2015)	$R = (dF_{cem}(t)/dt)/(F_{\max} - F_{cem}(t))$	R is the recovery rate; $F_{cem}(t)$ is the force or joint torque strength; $F_{\max}$ is the MVC of a muscle group in a given posture without fatigue.
Ye and Pan (2015)	$CRT = 0.414RBMI - 0.084PFA - 1.504PAR + 0.619HR_{\max} - 77.618$	CRT is the complete recovery time; $RBMI$ is the relative body mass index; PFA is the perceived functional ability; PAR is the physical activity rating; $HR_{\max}$ is the maximum heart rate.
Calzavara et al. (2019)	$RA = F(t_W)e^{-\mu\tau}$	$F(t_W)$ is the accumulated fatigue; t_W is the duration of the working activity; τ is the recovery time necessary for the operator to recuperate from the accumulated fatigue; μ is a physiological recovery alleviation factor.

Table 7
Classification by shift flexibility.

Shift design	Reference
Fixed	Barker and Nussbaum (2011), Geiger-Brown et al. (2012), Matthews et al. (2012), Plichta and Kelvin (2013), Han et al. (2014), Martin (2015), Cuevas et al. (2016), Yu et al. (2019a), Hong et al. (2019), Roets and Christiaens (2019)
Definable	Brunner et al. (2009), Rekik et al. (2010), Dietz (2011), Stolletz and Brunner (2012), Brunner and Bard (2013), Burke et al. (2013), Gunawan and Lau (2013), Wang and Ke (2013), Pisarski and Barbour (2014), Wang and Liu (2014), Todovic et al. (2015), Bowers et al. (2016), Veldhoven et al. (2016), Rahimian et al. (2017), Cheng et al. (2018), Hong et al. (2019), Shuib and Kamarudin (2019)

inal data, their model is built and the work sequence and number of breaks are determined. In order to find a joint staffing, routing, and payment policy that induces optimal service-system performance, Zhan and Ward (2019) assume that each server joins a queue of idle servers to access the next customer, and each rest period should have the same expected length. They solve for an approximate rest period length when customers are waiting in the holding area, and fixed value $b \geq 0$. Results show that a server may prefer to have longer and less frequent breaks rather than frequent short idle periods. Set in continuous time, the model of Baucells and Zhao (2019) formalizes the notion that fatigue accumulates with effort and decays with rest. Their model provides practical recommendations on how to mitigate fatigue using breaks to maximize productivity and increase workers' well-being and company profits.

As discussed in Section 3.1.2, Jaber and Neumann (2010) assume that fatigue increases linearly over time, and use MET to calculate the muscular recovery time. They describe a mixed-integer linear programming model that models fatigue and recovery in a dual-resource constrained system to support the identification of task schedules that optimise productivity without overloading system operators. Results show that short rest breaks after each task, short cycle times, and faster recovery rates improve system performance, and that reduced force levels in tasks reduce recovery needs. In Hsie, Hsiao, Cheng, and Chen (2009), fatigue increases exponentially with time. They use a formula associated with maximum oxygen consumption to predict the recovery time required when individual maximum acceptable work durations are exceeded in high-intensity work. A theoretical model and a GA-based mechanism are proposed for creating a work-rest schedule that balances the minimization of the time for completing jobs and the extra energy expended by workers. Jaber et al. (2013) provide a recovery model shown in Table 6. They assume fatigue accumulates exponentially with time, and a recovery break that must be of sufficient length to alleviate some of the accumulated fatigue. Results show that when a worker recovers faster from the accumulated fatigue, the sum of the production times for all tasks and the lengths of all production breaks reduces. Following the study of Jaber et al. (2013), Glock et al. (2019) and Jamshidi (2019) also consider residual fatigue. Glock et al. (2019) propose an exponential recovery model for managing a packaging process for small products on a production line. Results show that lower maximum permitted fatigue levels and larger workload lead to earlier and longer recovery periods, respectively. Jamshidi (2019) propose a nonlinear mathematical model that optimizes rest-break policy considering fatigue, to study its effects on reliability and associated costs in manufacturing systems. In Finco, Battini, Delorme, Persona, and Sgarbossa (2019), a new optimal method based on mixed integer linear programming and a new linearization methodology are proposed. They provide a detailed analysis of the impact that rest allowance evaluation can have on productivity, taking into account the rest allowance before, during and after an assembly balancing process.

The number, placement and length of rest periods also play an important role in transportation scheduling problems. Kok, Meyer, Kopfer, and Schutten (2010) propose a restricted dynamic programming algorithm for the vehicle routing problem with time windows and the full European social legislation on drivers' driving and working hours, where the break length between working periods must be at least 45 minutes if the day contains more than nine hours of working time. Rancourt, Cordeau, and Laporte (2013) develop and compare several scheduling algorithms for a vehicle routing problem with multiple time windows that combines scheduling rest periods for truck drivers. The quality of solutions can be improved by allowing the algorithm to split complete rests into partial rests.

4.2. Empirical studies in work-rest scheduling

A starting point for our review is the work of Konz (1998). He discusses fundamental mechanisms of fatigue, and presents a comprehensive survey of the work-rest scheduling literature. He classifies the work-rest scheduling literature associated with the skeletal muscular system according to static work and dynamic work. A rest allowance (RA) is defined as the time needed for adequate rest following a static exertion (see El Ahrache and Imbeau (2009); Ma et al. (2015); Perez et al. (2014)). Chan et al. (2012), Ye and Pan (2015), and Calzavara, Persona, Sgarbossa, and Visentin (2019) describe RA models for dynamic work. Table 6 lists rest allowance models for intermittent static muscular work and dynamic work.

Static work associated with awkward postures, with or without the application of force to an external object, results in fatigue. El Ahrache and Imbeau (2009) present a rest allowance model, shown in Table 6, to determine rest periods for static muscular work at manufacturing workstations. Their results show that shoulder fatigue is typically the determining factor in the required rest allowance. Perez et al. (2014) and Dode et al. (2016) develop and evaluate a methodology to predict levels of muscular fatigue in the shoulder region throughout the working day, by combining a discrete event simulation model of a real industrial system with empirically based MET and RA models. Ma et al. (2015) integrate time-related task parameters and individual attributes within a static work recovery model. The results show that their recovery model can be used to determine an effective work-rest cycle for each individual if the individual's recovery rate is known for a specific job. In dynamic work, muscles automatically create "micropauses", in contrast to the constant load of static work. High-intensity work is associated with higher perceived fatigue, which can be alleviated after a rest period. Ye and Pan (2015) propose a convenient model for predicting complete recovery time (CRT) after exhaustion in high-intensity work. Based on questionnaire results, their model obtains reliable estimates. Calzavara et al. (2019) integrate operator fatigue and recovery analysis into traditional decision support models for the design and management of production systems, and present an analytical model for setting the time necessary for operators to recover from the performed activity. Their model improves performance in terms of productivity.

Apart from considering flexible break length with a fixed number of breaks of work, the number of breaks with a fixed length of the rest break can also be determined. In Yi and Chan (2013), Monte Carlo simulation methods are used to optimize a work-rest schedule that balances labor productivity demands and the health and safety care of rebar workers in hot environments. They propose a schedule of a 15-minute break after working 120 minutes continuously in the morning, and a 20-minute break after working 115 minutes continuously in the afternoon. Hallbeck et al. (2017) study intraoperative microbreaks with stretching exercises in a non-crossover design. Results show that surgeons benefit from additional short microbreaks (1.5-2 minutes break every 20–40 minutes) during long operations. Chavaillaz, Schwaninger, Michel, and Sauer (2019) examine three work-rest schedules: spontaneous breaks (i.e., participants can take breaks at any time), and scheduled two 5-minute breaks and two 10-minute breaks during a 1-hour testing session. Results show no performance differences between break regimens, which suggests that there may be viable alternatives to the current EU regulations.

Activities at different pace and duration lead to different effects on the fatigue accumulation of workers and also different effects on recovery time, which emphasizes the need for flexible break length and flexible number of breaks. Roach, Petrilli, Dawson, and Lamond (2012) use mixed-model regression analysis to determine the effects of layover length on the amount of sleep that pilots obtain during a trip, and on pilots' subjective fatigue levels and capacity to maintain attention. They demonstrate that a short layover during a long-haul trip does not substantially disrupt pilots' sleep, but it may result in elevated levels of fatigue during and after the trip. Hence, if a short layover is used, pilots should have a minimum of four days off to recover. Chen and Xie (2014a) study the effects of the total duration of rest breaks, number of rest breaks, driving time from trip start to each rest break, and the duration of each rest break, by using the Cox proportional hazards model (Cox, 1972) and the model of Andersen and Gill (1982). Their results suggest that two 30-minute rest breaks are generally sufficient for a 10-hour trip, and additional rest breaks may not further reduce crash risk substantially, since they disturb drivers' working schedules. Further, Chen and Xie (2014b) use a discrete-time logistic regression model to evaluate the crash risks of driving time with rest breaks. They conclude that three or more rest breaks do not result in significant safety performance benefits to truck drivers, and drivers may need time to refocus after a rest break. Pasquale, Fruggiero, Iannone, and Miranda (2017) propose a human error probability analysis model for break scheduling assessment in manufacturing systems. Their model is useful in assessing the impact of different work-break policies, with different placement and duration of breaks, on human performance and on the overall system performance in terms of percentage of tasks performed successfully and economic results.

As indicated above, due to the inherent decay in human performance over time, it is necessary to integrate fatigue and recovery analysis into traditional scheduling models for the design and management of production systems. Rest breaks can be formally planned by organizational practices (e.g., coffee and lunch breaks) or informally taken by workers themselves. Both empirical and mathematical approaches to work-rest scheduling research focus on the length of rest breaks, and also address the number of rest breaks. Frequent short breaks are better than occasional long breaks. Concerning physical fatigue, the recovery level can be measured by using different physiological parameters such as HR and also mean and median frequency results from electromyography (EMG). Most RA models rely on estimation of the recovery time of the worker based on Maximum Holding Time (MHT) / MET or MVC. Faster recovery rates are associated with improved system performance, mostly due to productivity improvements. Scheduling research needs to incorporate all these issues, to create more valuable scheduling algorithms for practice.

4.3. Operational research approaches to shift scheduling

Definable shift scheduling addresses the assignment of starting and finishing times to employees. It allows flexibility of various types, including shifts of different durations and various starting times from a discrete set of available times. Many papers on definable shift scheduling are classified into mathematical programming categories such as integer programming, linear programming, dynamic programming and goal programming. To find an assignment that minimizes total overtime hours under fatigue-avoidance restrictions given by a labor agreement, Brunner, Bard, and Kolisch (2009) introduce a mixed-integer model for the flexible shift scheduling problem of physicians. Shifts are allowed to start at every pre-defined period in the planning horizon and extend up to 13 hours with an hour-long break included. Stolletz and Brunner (2012) develop a set covering formulation that requires shift patterns to be generated for a single day for the flexible shift scheduling problem of physicians at hospitals. They adjust the generated break assignment windows, keeping fixed the minimum number of periods before the break starts and after the break ends. Rekik, Cordeau, and Soumis (2010) develop two mathematical programming models of air-traffic controller shift scheduling problems, which include different forms of flexibility for shift starting times, break lengths, and break placement, to explore the impact of fractional breaks and work duration restrictions. Their results show that, for some instances, the use of splittable breaks considerably reduces the workforce. For workers in the service sector generally, the model proposed by Dietz (2011) includes the capability to limit the fraction of agents who are assigned to split shifts. For situations where call volume is high, he integrates queueing theory, quadratic programming, and a variable-threshold rounding algorithm to find server assignments that maximize the fraction of call requests that receive service. Cuevas, Ferrer, Klapp, and Muñoz (2016) propose a mixed integer programming model that solves the short-term multi-skilled workforce tour scheduling problem. This model enables decision makers to design the workday, break lengths, and shift assignments, to maximize and balance staff coverage across multiple activities.

The definable shift scheduling problem also allows the addition of constraints based on problem-specific requirements. Incorporating rostering and resource constraints together with complex physician preferences, Gunawan and Lau (2013) study the operations of a hospital; this is the master physician scheduling problem. Due to fatigue, a physician assigned to a heavy duty in a particular shift cannot be assigned to a different heavy duty in the next shift. The optimal solutions obtained by the mathematical programming models satisfy many physicians' preferences and duty requirements, while ensuring optimum usage of available resources. Bowers, Noon, and Wu (2016) incorporate individual shift preferences into a physician rostering model. They describe a hybrid version of the model that simultaneously accommodates some physicians who prefer an equitable schedule, and others who are willing to deviate from the equitable schedule to fit their personal shift preferences. Their method accommodates different worker preferences among shift types. Allowing for constraints and worker preferences, Rahimian, Akartunal, and Levine (2017) present a hybrid algorithm, which combines integer programming and constraint programming to solve a highly-constrained nurse rostering problem. They assume that all rosters are for seven days including two rest days. Hong et al. (2019) consider the problem of assigning medical residents to shifts within a pediatric emergency department. They show that integer programming techniques, in combination with discussions with the chief residents, achieve good outcomes. To reduce air traffic controller fatigue, Wang and Ke (2013) develop an integer programming model that considers holidays and manpower requirements, to determine optimal work shift schedules. They show how an air traffic controller's state recovers to approximately the initial state after a cycle of average work and rest hours. Using a mixed-integer program, Wang and Liu (2014) find a feasible work shift schedule that minimizes the peak fatigue of shift workers while satisfying their days-off requirements. This model delivers schedules that are apparently easier to implement than those of Wang and Ke (2013). Addressing the problem of flexible shift scheduling of service employees at mail processing centers, Brunner and Bard (2013) develop an efficient branch and price algorithm. They find that the required size of the workforce is most sensitive to lunch break requirements. If a service system has sufficient slack, lunch breaks can be incorporated on an ad hoc basis. Todovic, Makajic-Nikolic, and Kostic-Stankovic (2015) focus on determining an optimal allocation of police officers in accordance with the required division and assignment of labor. Their mixed integer programming model designs a schedule where police officers work over three shifts. Shuib and Kamarudin (2019) formulate a binary integer goal programming model for the shift scheduling problem that optimizes power station workers' days-off preferences. Their study involves scheduling 43 workers over 28 days, where workers work in morning, evening, and night shifts, and have standby and rest days. Their model generates optimal schedules, satisfies days-off preferences and provides workers with a chance to work with different groups.

For problems such as nurse rostering that involve a high degree of flexibility in shift starting times, shift lengths, or the timing of breaks, the number of possible shifts may be very difficult to enumerate using exact methods. To circumvent this difficulty, Brucker, Burke, Curtois, Qu, and Vanden Berghe (2010) describe a heuristic decomposition approach which first constructs high quality sequences and then uses these sequences to incorporate schedule and roster constraints. Veldhoven et al. (2016) also study a decomposition approach for the personnel scheduling problem. This approach first solves the days-off scheduling problem, which assigns working days and days off to a set of employees, and then assigns specific shifts, e.g., early or late, to working days in the days off schedule. This decomposition produces good solutions for most instances in reasonable computation time. Burke, Curtois, Qu, and Vanden Berghe (2013) first define single neighborhood swaps, and then use heuristic rules to determine which of those to extend into larger swaps. They find that creating a high-quality roster can increase job satisfaction and diminish fatigue, and hence result in improved patient care. Their results appear to beat all previous approaches for quality of solution. Work shifts are commonly used in construction projects to meet project deadlines. Cheng, Huang, and Hutomo (2018) design a work shift scheduling model using chaotic search particle swarm optimization. Their model generates schedules that balance the project duration and cost, while scheduling as few evening and night shifts as possible. Interestingly, they show that cycling two different groups of employees every four days reduces fatigue. Also, they observe that shift work during the evening and night is typically more efficient due to the quieter, less congested environment.

4.4. Empirical studies in shift scheduling

In general, employees prefer constant starting times because they provide a better work-life balance (Brunner et al., 2009). A shift pattern is identified by its starting day, shift timing (i.e., day, evening, or night), and shift length (i.e., 8-hour shifts or 12-hour shifts). Typically, hospitals in the U.S. hire nurses to work one of five regular shifts: 8-hour shifts starting at 7:00 AM (day shift), 3:00 PM (evening shift), or 11:00 PM (night shift), or 12-hour shifts starting at 7:00 AM (day shift) or 7:00 PM (night shift). A survey by Barker and Nussbaum (2011) measures psychological, physiological, and total fatigue dimensions, acute and chronic fatigue states, and job performance. Their Analysis of Variance (ANOVA) results indicate that nurses working shifts longer than 8 hours report higher fatigue levels and lower performance, compared with those working 8-hour shifts. Also, nurses working longer shifts are more than three times more likely to commit an error. Han, Trinkoff, and Geiger-Brown (2014) study 175 American full-time female 12-hour shift nurses from medical, surgical and critical care units. They find that nurses working variable and unpredictable shift patterns have higher fatigue levels, compared to those working regular fixed shifts. However, some studies find that 12-hour shifts reduce nurses' fatigue levels due to better quality downtime. Geiger-Brown et al. (2012) focus on nurses who work 12-hour shifts. Sleepiness (on the KSS) and vigilance (on the Performance Vigilance Task measure) are estimated over time for 80 registered nurses. The inter-shift recovery of 12-hour shift nurses averages only 40% between shifts, but the levels of acute and chronic fatigue are lower than those reported in other studies (e.g., Barker & Nussbaum (2011)). In Martin (2015), the Wilcoxon matched-pairs test (Plichta & Kelvin, 2013) is used to examine the effect of working 8-hour shifts versus working 12-hour shifts on nurse fatigue (based on acute, chronic, and inter-shift recovery) and job satisfaction. Here, 8-hour shifts are associated with higher fatigue levels in the long run, due to more workdays and greater weekly commuting time. Yu, Somerville, and King (2019a) help nurses in Intensive Care Units (ICU) recognise and understand the impact of 12-hour shifts on their fatigue levels. This study find that the majority of ICU nurses in both hospitals had low to moderate fatigue levels, indicating that they adapt well to 12-hour shifts.

The shift work at Traffic Control Centers of Belgian Railways is standardized using 8-hour shifts, starting at 06:00, 14:00 and 22:00. Matthews et al. (2012) explore the extent to which fatigue and driving performance during the early-morning hours (i.e., 4:00 a.m. to 8:00 a.m.) differs from that during other shifts. Mixed-model ANOVA reveals that this particular period is of importance, since driving performance (i.e., lane violations, lane position variability, and speed variability) is worst at that time. Roets and

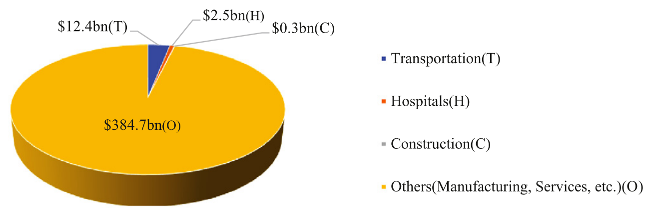

Fig. 2. Cost of fatigue among safety-critical application areas.

Christiaens (2019) analyze a full-year data set for a railway traffic control system. Their regression results show that the probability of making at least one error is highest on Saturdays (+ 6% probability compared to Mondays), and lowest on Tuesdays, Wednesdays and Thursdays. Hence, safe schedule design should consider the day of the week.

Shift lengths and various shift schedules (e.g., day vs. night shifts) result in differences in fatigue levels and performance. Pisarski and Barbour (2014) examine shiftworkers' fatigue and the longitudinal relationships that impact on fatigue such as team climate, work life conflict, control of shifts and shift type in shift working nurses. Their findings suggest that control over shift scheduling can have significant effects on fatigue for both two-shift and three-shift workers.

As discussed above, workload, shift timing, shift duration, direction of shift rotation, and number and length of breaks during and between shifts are the main factors in optimizing shift systems for the workplace. Example costs include regular and overtime wages, penalties for not meeting employee preferences, and penalties for unequal distribution of employees to shifts. The most commonly studied performance measure involve makespan, total completion time, total weighted completion time, maximum lateness, maximum tardiness and number of tardy jobs. Example constraints for each employee include the maximum number of daily hours scheduled, the minimum number of weekly hours scheduled, and the maximum number of consecutive days scheduled without days off. One way of making the schedule attractive to workers is to limit the number of assignments per day (e.g., the number of jobs done per day, which comes down to limiting the number of switches per worker) or per week (typically the number of active shifts per week is limited). Various guidelines can be applied to design shiftwork, for example:

(i). Avoid a start before 7 A.M. for the morning shift.
(ii). Allow sufficient time for sleep between shifts.
(iii). Limit the number of consecutive working days to 5–7.
(iv). Allow some weekends with at least two consecutive full days off.

These measures, individually or in combination, can substantially mitigate fatigue.

5. Applications

As discussed in Section 1, the costs of fatigue in U.S. industry are very substantial. According to the National Safety Council, there are also significant differences in the relative cost of fatigue between the safety-critical application areas of transportation, hospitals, and construction, and others (manufacturing, services, etc.) (see Fig. 2). The classification according to application areas identifies the relative importance of fatigue as a major contributor of cost. As shown in Table 8, we divide the works reviewed into five application areas, i.e., manufacturing, construction, transportation, hospitals and services, and then discuss differences in fatigue origination and mitigation among these application areas.

In traditional manufacturing industry, various manual tasks such as lifting, lowering, pushing and pulling, holding or carrying objects or materials are carried out during activities such as manual order picking in warehouses and manual feeding of materials to assembly and production work-stations. Workers are required to perform repetitive tasks using specific muscle groups. Fatigue can have a substantial impact on the performance of a manufacturing system (Battini et al. (2016); Calzavara, Persona, and Sgarbossa (2018); Ma et al. (2015)). Through the use of advanced technologies, production methods and scope have undergone fundamental changes that have reduced physiological fatigue but increased psychological fatigue (Monteiro, Skourup, & Zhang, 2019). Heart rate is apparently the best measure for monitoring the physiological fatigue of operators within an industrial context. Compared to manufacturing workers, construction workers often perform jobs that involve over-exertion and awkward postures in uncontrolled outdoor working environments with limited use of machinery. For this reason, many researchers in this area study the overall physical fatigue of construction workers rather than localized muscular fatigue (e.g., Aryal et al. (2017); Seo et al. (2016)). There are several effective means of measuring psychological fatigue at construction sites (e.g., Fang et al. (2015); Li et al. (2019a); Techera, Hallowell, Littlejohn, and Rajendran (2018); Zhang et al. (2015)). Subjective feedback scales help researchers and practitioners to understand better the typical fatigue symptoms of construction workers. In transportation, the monotony and sedentary nature of long distance driving pose a high risk of fatigue. This is sometimes exacerbated by high density traffic and time of day; driving performance is known to be at its worst during the early morning hours for road and rail transport operations. Hence, several fatigue detection and measurement technologies are designed specifically for vehicle operators (see Dawson, Searle, and Paterson (2014); Lerman et al. (2012)). Hospitals face uneven workload distributions over time, which makes shift scheduling difficult. Their staff frequently complete long working hours with a combination of both physically and mentally demanding tasks, which may lead to increased levels of multidimensional fatigue and to both acute and chronic fatigue states (Kc & Terwiesch, 2009; Lin, Sir, Sisikoglu, Pasupathy, & Steege, 2013; Steege et al., 2018). The OFER scale is used to measure the fatigue states present. Also various quantitative approaches are used to estimate fatigue levels. What makes fatigue management in the service sector more difficult than in other applications is the wide fluctuations in demand that occur randomly throughout the day and across different days. The performance of many service organizations is sensitive to the starting time of each shift and lunch break requirements. Service times (Wang et al., 2014), service slowdowns (Dong et al., 2015) and overwork (Delasay et al., 2016) are useful as measures of fatigue here.

Some work-rest models and shifts and policies discussed in our literature review are effective in reducing fatigue levels among workers in manufacturing (e.g. Calzavara et al. (2019); Dode et al. (2016); Zhao et al. (2019)), construction (e.g. Cheng et al. (2018); Krzeminski (2017); Li, Chow, Zhu, and Lin (2016)), transportation (e.g. Chang et al. (2019); Roets and Christiaens (2019); Wang and Ke (2013)), hospitals (e.g. Bowers et al. (2016); Hong et al. (2019); Rahimian et al. (2017)), and services (e.g. Shuib and Kamarudin (2019); Sun and Whitt (2018); Zhan and Ward (2019)), and improving job performance. Service organizations that operate within the normal 8-hour day and face low or medium congestion levels, typically use pre-planned rest break schedules. However, compared to other application areas, pre-planned rest schedules for transportation may be a less effective means of counteracting the accumulation of fatigue over prolonged periods behind the wheel. For the five application areas we discuss, evaluating the level of muscle fatigue prior to work and implementing appropriate interventions to

Table 8
List of papers per application area.

Application area	Reference
Manufacturing	El Ahrache and Imbeau (2009), Ma et al. (2009), Jaber and Neumann (2010), Ozturkoglu and Bulfin (2012), Michalos et al. (2013), Perez et al. (2014), Zhang et al. (2014), Ma et al. (2015), Ye and Pan (2015), Battini et al. (2016), Dode et al. (2016), Mossa et al. (2016), Chowdhury and Nimbarte (2017), Ferjani et al. (2017), Pasquale et al. (2017), Sobhani et al. (2017), Calzavara et al. (2018), Tiacci (2018), Calzavara et al. (2019), Glock et al. (2019), Otto and Battaia (2019), Zhao et al. (2019)
Construction	Hsie et al. (2009), Chan et al. (2012), Yi and Chan (2013), Fang et al. (2015), Zhang et al. (2015), Li et al. (2016), Seo et al. (2016), Yi et al. (2016), Aryal et al. (2017), Krzeminski (2017), Cheng et al. (2018), Techera et al. (2018), Li et al. (2019a), Yu et al. (2019b), Zhang et al. (2019)
Transportation	Gershon et al. (2009), Jap et al. (2009), Yang et al. (2010), Atchley and Chan (2011), Lerman et al. (2012), Matthews et al. (2012), Roach et al. (2012), Unal, Steg, and Epstude (2012), Zhao et al. (2012), Rancourt et al. (2013), Wang and Ke (2013), Chen and Xie (2014a), Chen and Xie (2014b), Dawson et al. (2014), Wang and Liu (2014), Fu et al. (2016), Yildi et al. (2017), Bowden and Ragsdale (2018), Chang et al. (2019), Roets and Christiaens (2019)
Hospitals	Brunner et al. (2009), Kc and Terwiesch (2009), Brucker et al. (2010), Barker and Nussbaum (2011), Geiger-Brown et al. (2012), Stolletz and Brunner (2012), Burke et al. (2013), Lin et al. (2013), Gunawan and Lau (2013), Martin (2015), Van Huele and Vanhoucke (2014), Bowers et al. (2016), Rahimian et al. (2017), Steege et al. (2018), Hong et al. (2019)
Services	Dietz (2011), Brunner and Bard (2013), Wang et al. (2014), Tan and Netessine (2014), Dong et al. (2015), Todovic et al. (2015), Cuevas et al. (2016), Delasay et al. (2016), Delasay et al. (2019), Shuib and Kamarudin (2019), Zhan and Ward (2019)

Table 9
Classification based on type of data and level of implementation.

Data included in the scientific work	Reference
No testing	Lerman et al. (2012), Dawson et al. (2014), Delasay et al. (2016), Steege et al. (2018), Tiacci (2018), Otto and Battaia (2019), Roets and Christiaens (2019), Zhan and Ward (2019)
Artificial data	Brunner et al. (2009), El Ahrache and Imbeau (2009), Hsie et al. (2009), Ma et al. (2009), Brucker et al. (2010), Yang et al. (2010), Atchley and Chan (2011), Dietz (2011), Stolletz and Brunner (2012), Ozturkoglu and Bulfin (2012), Burke et al. (2013), Brunner and Bard (2013), Gunawan and Lau (2013), Wang and Ke (2013), Van Huele and Vanhoucke (2014), Wang et al. (2014), Wang and Liu (2014), Tan and Netessine (2014), Dong et al. (2015), Todovic et al. (2015), Bowers et al. (2016), Cuevas et al. (2016), Dode et al. (2016), Ferjani et al. (2017), Pasquale et al. (2017), Yildi et al. (2017), Bowden and Ragsdale (2018), Shuib and Kamarudin (2019), Zhao et al. (2019)
Real-world	El Ahrache and Imbeau (2009), Gershon et al. (2009), Jap et al. (2009), Kc and Terwiesch (2009), Jaber and Neumann (2010), Barker and Nussbaum (2011), Chan et al. (2012), Geiger-Brown et al. (2012), Matthews et al. (2012), Roach et al. (2012), Zhao et al. (2012), Lin et al. (2013), Michalos et al. (2013), Rancourt et al. (2013), Yi and Chan (2013), Chen and Xie (2014a), Chen and Xie (2014b), Perez et al. (2014), Zhang et al. (2014), Fang et al. (2015), Ma et al. (2015), Ye and Pan (2015), Zhang et al. (2015), Battini et al. (2016), Fu et al. (2016), Li et al. (2016), Mossa et al. (2016), Seo et al. (2016), Yi et al. (2016), Aryal et al. (2017), Chowdhury and Nimbarte (2017), Rahimian et al. (2017), Sobhani et al. (2017), Calzavara et al. (2018), Cheng et al. (2018), Techera et al. (2018), Calzavara et al. (2019), Chang et al. (2019), Delasay et al. (2019), Glock et al. (2019), Hong et al. (2019), Li et al. (2019a), Yu et al. (2019b), Zhang et al. (2019)
Applied in practice	El Ahrache and Imbeau (2009), Jaber and Neumann (2010), Rancourt et al. (2013), Perez et al. (2014), Zhang et al. (2014), Bowers et al. (2016), Mossa et al. (2016), Yi et al. (2016), Calzavara et al. (2018), Calzavara et al. (2019), Hong et al. (2019)

reduce physical demands helps to prevent the adverse effects of workers' fatigue.

6. Data and implementation

We discuss various approaches, as shown in Table 9, to the sourcing and usage of data in operational research on fatigue, within the five application areas, i.e., manufacturing, construction, transportation, hospitals and services, shown in Table 8. Many studies are tested with artificial data and a few works reviewed do not use data. Sometimes a model is tested with real data, but not applied in practice. Models that are implemented may be used only experimentally or temporarily, or alternatively may become part of an ongoing planning system.

In order to develop a fatigue model, as discussed in Section 3, many researchers include a measurement phase to predict the level of fatigue. The majority of papers on fatigue measurement and prediction use real-world, rather than artificial, data. In manufacturing, Zhang et al. (2014) conduct single arm pushing experiments in an electronics factory to assess muscular fatigue using the theoretical models of MET developed by Ma et al. (2009). A laboratory-based experiment is performed by Chowdhury and Nimbarte (2017) to study neuro-muscular fatigue by simulating arm exertions. Calzavara et al. (2018) use heart rate monitoring, both in a laboratory context and in a real industrial context for the evaluation of its effectiveness. Four practical cases are investigated by Jaber and Neumann (2010) in a dual-resource constrained system for the effects of fatigue and recovery. Based on a case study from industry, Perez et al. (2014) use biomechanical analysis to quantify workloads at the workstation level, and a discrete event simulation model to obtain system level patterns of production cycles. Mossa, Boenzi, Digiesi, Mummolo, and Romano (2016) present a case study from the automotive industry, and the related human workload balancing problem for repetitive manual tasks is solved in order to test the reliability of their model. The modeling framework of Sobhani et al. (2017) is numerically analyzed according to fatigue data from General Motors of Canada. In construction, Fang et al. (2015) use indoor laboratory experiments to study the effect of fatigue on construction workers' safety performance. Li et al. (2016) measure labor productivity data related to direct work time, indirect work time and idle time for two construction projects involving 16 rebar workers in Beijing. In order to validate the early warning system for risk assessments of extreme fatigue, Yi et al. (2016) conduct a controlled experiment during summer time at a construction site. Aryal et al. (2017) collect physiological data from 12 construction workers in an experiment in which they simulate a material handling task to monitor fatigue. Techera et al. (2018) conduct a field study of 252 U.S. construction workers in which potential fatigue predictors are assessed. In Glock et al. (2019), fatigue parameters are derived from an experiment simulating a packaging process. Yu et al. (2019b) conduct a laboratory experiment to test the accuracy of the 3D motion estimation method for fatigue monitoring in construction work. Seo et al. (2016) use a case study of masonry work to demonstrate the value of integrating muscle fatigue assessment into operational planning. Using a survey, Zhang et al. (2015) assess the severity of fatigue among construction workers. In hospitals, Kc and Terwiesch (2009) validate their models based on a sample of 2740 patients corresponding to all admissions. A cross-sectional study of 745 nurses from different nursing organisations by Barker and Nussbaum (2011) finds a link between shift length and fatigue, and between fatigue and job performance. In transportation, Michalos, Makris, and Chryssolouris (2013) present a case study from the heavy vehicles assembly sector. Simulation experiments based on real data are performed by Li et al. (2019a) and Zhang, Diraneyya, Ryu, Haas, and Abdel-Rahman (2019) in construction; Jap et al. (2009), Gershon, Ronen, Oron-Gilad, and Shinar (2009), Zhao et al. (2012), Fu et al. (2016), and Chang et al. (2019) in transportation; and Delasay et al. (2019) in services, to evaluate fatigue.

Researchers also use real-world data to show the applicability of fatigue models and solutions. In manufacturing, through theoretical and experimental validation, with a total number of 20 young male subjects recruited from a factory, the proposed recovery model of Ma et al. (2015) estimates exponential recovery. Ye and Pan (2015) use a laboratory test with 47 young adult subjects to evaluate their proposed recovery time prediction model. In Battini et al. (2016), a simple numerical example for a real case is presented to analyze the behavior of Pareto frontiers by varying several parameters linked to energy and time value. In construction, Chan et al. (2012) collect 411 sets of meteorological and physiological data over fourteen working days to derive optimal recovery times for rebar workers. Yi and Chan (2013) use field studies and provide an objective mechanism to optimize work-rest schedules that balance labor productivity demands and the health and safety care of rebar workers in hot environments. Cheng et al. (2018) employ a real case to verify the robustness and efficiency of their proposed approach for the work shift problem. Calzavara et al. (2019) apply a model for fatigue evaluation and rest allowance estimation to a simple example using data from a real case study. In hospitals, Geiger-Brown et al. (2012) perform neurobehavioral testing under actual working conditions of 80 registered nurses. Lin et al. (2013) use real patient census data and various surveys of nurses working in different hospitals. Rahimian et al. (2017) test their algorithm using two different datasets consisting of various problem instances, showing that the proposed algorithm is able to solve a wide variety of instances effectively. Hong et al. (2019) also apply experience from a hospital in building monthly schedules to solve residency scheduling problems. In transportation, Matthews et al. (2012) assess the driving performance of 41 male participants on a 10-minute simulated driving task with the standard deviation of lateral position measured. Rancourt et al. (2013) test their proposed algorithms for a vehicle routing problem with multiple time windows on a real-life instance. Chen and Xie (2014a) use a real data set to study the impact of off-duty time prior to a trip. Chen and Xie (2014b) use data collected from two national truckload carriers to evaluate the crash risks of driving time with the influence of rest breaks. In services, the study of Shuib and Kamarudin (2019) involves scheduling 43 workers in a department of a power station for 28 days where workers work in morning, evening and night shifts and have standby and rest days.

There are also situations where, due to unavailability of real world data, researchers use artificial data. Hsie et al. (2009) test several examples to determine the efficiency of their proposed model for creating a work-rest schedule for construction workers. Yang et al. (2010) validate a proposed dynamic Bayesian network model to predict fatigue in a simulated driving environment. Atchley and Chan (2011) use a driving simulator to investigate the effects of a concurrent verbal task. El Ahrache and Imbeau (2009) select tasks from a database to determine rest periods for static muscular work in manufacturing workstations. In the paper of Ma et al. (2009), a virtual reality framework is constructed to apply a fatigue index in a virtual environment for digital work evaluation. Dode et al. (2016) use discrete event simulation to predict productivity and quality. In the paper of Ferjani et al. (2017), a job shop system is simulated to illustrate the proposed approach. Pasquale et al. (2017) use a simulator to model human error probability analysis for break scheduling problems. Ozturkoglu and Bulfin (2012) use numerical examples to analyze the performance of an exact mathematical model and a heuristic algorithm for determining break times. Zhao et al. (2019) use numerical examples to validate a genetic algorithm based mechanism and a mathematical model for creating a work-rest schedule. Similarly, Yildi et al. (2017), Bowden and Ragsdale (2018), Wang and Ke (2013), Wang and Liu (2014) in transportation, and Brucker et al. (2010), Burke et al. (2013), Brunner et al. (2009), Stolletz and Brunner (2012), Gunawan and Lau (2013), Bowers et al. (2016), Van Huele and Vanhoucke (2014) in hospitals, and Todovic et al. (2015), Dong et al. (2015), Tan and Netessine (2014), Wang et al. (2014), Brunner and Bard (2013), Dietz (2011), Cuevas et al. (2016) in services, provide several examples to demonstrate the effectiveness of their proposed approaches.

7. Research opportunities

The operational research methods discussed in this work have great potential to improve the understanding of fatigue, and to improve the design of work schedules and systems to mitigate fatigue and thus enhance the productivity and quality of work. Many research opportunities are identified from the above literature and presented in Table 10. New measures of fatigue, digital and connected technologies, and advances in operational research, are all significantly influencing the prevention and reduction of fatigue. Meanwhile, the application areas of manufacturing, construction, transportation, hospitals, and services, frequently characterized by challenging work environments, require active management of fatigue. Based on our findings and insights from the above literature review, we discuss several research opportunities that are of the greatest practical and theoretical interest.

First, the development, testing and implementation of integrated, systems-based fatigue detection technology to monitor worker performance is a priority research area for the future. As we discuss in Section 3, localized muscular fatigue can be measured using the SEMG, MVC or EEG; and multiple muscular fatigue can be measured using the HR, MET or similar metrics. In applications requiring more mentally demanding work, such as transportation, hospitals, and services, fatigue is measured using detection technologies, which have become increasingly computerised. Here, intelligent devices save production costs and enhance economic efficiency; however, the imperfections of existing technology and equipment still require the participation of workers in the process, which is distracting and paradoxically induces fatigue. Enhancing the interaction of technology and personnel to reduce fatigue while maintaining productivity is an important problem to be solved. For example, measures related to the autonomic nervous system, such as heart rate variability and pupil diameter, and event-related brain potential (ERP) can be developed to monitor psychological fatigue in service operations.

Second, models can be developed for dynamic analysis of employee-related work efficiency. Integrating fatigue into scheduling problems, using additional decision variables and more general objective functions is discussed within our literature review. Example decision variables include (i) the number, placement, and duration, of rest breaks, and (ii) the length of shift. Relevant objectives include: (i) minimizing cumulative fatigue associated with

Table 10
Summary of opportunities for future research.

	Research Opportunities	Proposed by
Fatigue measurement	Combining other factors (Circadian rhythm, different time zones, etc.) into an overall optimization fatigue framework; developing better objective methods for fatigue prediction; developing better fatigue detection technologies (fitness for duty and real-time assessment devices).	Ma et al. (2009), Zhang et al. (2014), Ye and Pan (2015), Glock et al. (2019), Yu et al. (2019b)
Fatigue mitigation	Using hybrid approaches for fatigue management; estimating work-related residual fatigue; accounting for fatigue in worker recovery; determining how fatigue detection technologies and biomathematical scheduling tools can be incorporated together; incorporating environmental factors into work-rest models; addressing individual differences in response to fatigue; exploring efficacy of informal fatigue risk mitigation strategies (task rotation, shifts, etc.) in various areas; addressing the interaction of intershift recovery with time off between shifts, workload, and workplace performance.	Dietz (2011), Jaber et al. (2013), Dong et al. (2015), Dode et al. (2016), Pasquale et al. (2017), Sobhani et al. (2017), Sun and Whitt (2018), Calzavara et al. (2019), Delasay et al. (2019), Hong et al. (2019), Roets and Christiaens (2019)

performing a task, and (ii) minimizing the number of human errors during a shift. However, there remain concerns around the validity of many existing fatigue and recovery models in different applications. To be effective, the fatigue level in the model must be responsive to empirical data, so that the break times and frequencies recommended by the model are effective and implementable. For example, through the fatigue measurements discussed in Section 3, large amounts of data are collected and used in fitting functions to calibrate a dynamic evaluation model of employee fatigue and thereby improve employee-related work efficiency. Also, independent reliability and validity studies need to be undertaken on many fatigue detection devices, using large samples from a variety of demographic backgrounds and various health issues. Finally, the use of empirical data in deterioration scheduling would help translate theoretical gains into practice.

Third, the development of new multi-objective optimization approaches for fatigue recovery, to consider alternative human factor measures, would be valuable. The goals of scheduling problems include minimizing tardiness penalty costs, minimizing the difference between workload and assignments, and minimizing the number of part-time workers. Future research questions can be addressed using multiple objectives, for example the interaction of intershift recovery with time off between shifts, workload, and workplace performance. Much remains to be discovered about these complex and important tradeoffs.

Fourth, in manufacturing, construction, and hospitals, preplanned personnel scheduling, including shift scheduling, is valuable in detecting early signs of fatigue before unsafe levels are reached. In many situations, fatigue can be addressed using either a *proactive* or a *reactive* approach (Van Dongen, 2018). A proactive approach focuses on eliminating fatigue problems before they appear; whereas, a reactive approach is based on responding to fatigue after it has occurred. Many fatigue countermeasures are applied reactively, which is typically more expensive. Effective work-rest strategies in reducing accumulated fatigue and improving operational performance need further computational validation (Glock et al. (2019); Jaber et al. (2013); Visentin, Sgarbossa, Calzavara, and Persona (2018)). In proactive approaches, organizations have strategies in place to minimize the occurrence and severity of fatigue using a combination of discrete event simulation and human factors modelling (Dode et al. (2016); Perez et al. (2014)) or preplanned personnel scheduling (Geiger-Brown et al. (2012); Roets and Christiaens (2019)). These approaches allow system designers to understand the fatigue-related effects of proposed alternatives at the system design stage, where change is easier and cheaper than it is later. This motivates the use of early warning systems for collecting timely information and undertaking fatigue risk assessments. Further, it would be valuable to study large-scale preplanned personnel scheduling problems that cannot be solved efficiently by exact optimization models, by using metaheuristic or evolutionary approaches.

Fifth, multitasking models can be used to estimate the cost effect of multitasking proactively, in order to evaluate tradeoffs in allowed workplace procedures that may alleviate psychological fatigue. Multitasking is an additional option that can be used as an alternative to RMA to recover or mitigate some of the negative effects of fatigue (Hall et al., 2015; Zhu et al., 2017). The models of alternating work patterns and concurrent work design developed by Hall, Leung, and Li (2016) provide potential ways to alleviate fatigue through multitasking. Here again, greater use of empirical data is needed. This is an important topic for future study within operational research.

Finally, task scheduling optimization models, based on human-machine cooperation mechanisms, can effectively integrate the planning of workers and the performance of machines, and thereby proactively reduce the occurrence of work-related fatigue. Modern industry is supported by advanced science and technology, and its production methods, production modes and production scales continue to change. Integrated, flexible, reconfigurable, digital and intelligent production methods are replacing traditional methods of production. Concurrently, production modes are changing from high volume and small variety to customized production and agile manufacturing, hence the role of a worker in task-oriented human-machine interaction is changing from that of operator to that of decision-maker or supervisor. As discussed in Section 4, models that integrate RMAs and sequence-dependent processing times provide pathways towards deterministic modeling of fatigue reduction. Similarly, stochastic modeling frameworks, which involve scheduling models with random machine breakdowns and deterioration processes; scheduling models with sequence-dependent processing times; and work-rest scheduling models, all have the potential to generate improved performance outcomes. Analysis of dynamic job shop production systems, combined with the actual needs of the enterprise, presents a valuable opportunity for scheduling optimization models with human-machine collaboration.

8. Concluding remarks

This paper provides a focused review of the literature of fatigue, its effect on operational performance, and the use of operational research to mitigate it. The study of fatigue is complex, due to its close relation to several branches of the operations literature, the variety of ways in which it arises in diverse applications, and the range of possible approaches that are proposed to avoid or mitigate it. We document a recent increase in research interest in this topic, which apparently originates from several causes. A first cause is broader understanding of the substantial costs of fatigue, both immediately for the efficiency and quality of work, and in the longer run for employee health. A second cause is the improved modeling and solution capabilities of operational research approaches to addressing fatigue. A third cause is the development of improved fatigue-monitoring technology, for example motion capture and eye closure detection. A fourth cause is an increased understanding that proactive avoidance of fatigue is both cheaper and more effective than reactive mitigation of fatigue; this understanding motivates the design of less stressful work schedules. A fifth cause, the effects of which are as yet not fully realized, is increased concern by companies for the work-life balance of their employees.

We discuss the literature of fatigue within the context of several related topics: work-rest scheduling, shift scheduling, multitasking, ergonomics, deterioration scheduling, and occupational health and safety. We classify the literature of fatigue across multiple dimensions: the methods by which it is identified and measured; the operational research methodology applied for fatigue prevention or mitigation; the flexibility allowed in work-rest scheduling and also in shift scheduling; applications within manufacturing, construction, transportation, hospitals, and services; and the extent to which real data is used and results are implemented.

We identify numerous valuable contributions of operational research to the avoidance and mitigation of fatigue. We also identify many important research directions for operational research in this context, to promote its broader and more effective use to mitigate the effects of fatigue on operational performance. These include the development of improved methods for predicting and measuring fatigue more precisely. The estimation of recovery periods, especially under residual fatigue from previous shifts, needs to be enhanced by more empirical work. More general operational research models for work-rest scheduling can include optimization of both duration and timing of breaks. In conclusion, we view the "next frontier" of work on this topic as being the development of fatigue prediction, measurement and mitigation models within operational research that are calibrated for *individual workers*. Although challenging, this is a direction that has potential for great research opportunities and practical benefits.

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