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Towards Dynamic and Adaptive Allocation of Staff in a Digital-organized Production Context: An Innovative Perspective from Work Science

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Abstract

The increasingly complex socio-technical systems in modern businesses are forcing us to adapt our risk management models to a context of digital-organized production. This new phase of industrial digitization is bringing new opportunities and new challenges for managers and workers. A new work organization is emerging, along with new models for optimizing the allocation of labor to production activities. Three approaches are proposed in the literature: Mathematical optimization, models from work sciences, and integration of these two. Integrated analytical models are limited both by the number of variables considered and knowledge of the associated uncertainties. These models are static, not always focused on reducing risks at the source, and based on expert elicitation by unspecified protocols. Advances in this field are raising several questions regarding ethics, legality and safety. A model that allows systematic reduction of occupational health and safety risks and dynamic integration of operational considerations is needed. Successful businesses in the future will rely on managerial approaches that are interdisciplinary, focused on human wellbeing and draw on smart technologies and artificial intelligence.

Keywords: Work science; Job rotation; Industry; Smart factory; Digital factory; Digital-organized production; Smart production; Smart manufacturing

Introduction

Modern business operations (e.g. aircraft de-icing centre, aeronautical assembly plant, underground mine, bronchoscopy service, aircraft assembly line) have become complex socio-technical systems [1,2]. They involve numerous and diverse interdependent risks that intersect a wide range of disciplines and require taking into account uncertainty and the expectations of several categories of social actors. Risks must be prioritized on the basis of multiple factors and managed using means optimized for the particular context. They must be integrated using an interdisciplinary approach [2], indeed an inter-sector approach, and physical dangers as well as long-term health hazards must be eliminated [3,4]. Economic uncertainty, increasingly fierce international competition, acceleration and enhancement of product and service personalization as well as shortening of product and service lifecycles are additional new realities facing our businesses. In this context, a production system, that is, the equipment, the supply chain and the human resources, must all be more responsive and versatile [1,5].

In most of the organizations studied, strategic planning of production has been based on managing labor versatility using primarily three strategies: dynamic staffing through hiring, laying off (or dismissal) and part-time work, paying work crews for overtime, or maintaining extra work crews, sometimes on atypical work schedules. Job rotation programs have been tested as well, in the wake of the lean manufacturing movement or in attempts to manage exposure to factors causing musculoskeletal injuries. In the latter case, the results are not convincing, according to the most recent review of the literature [6]. The inadequacy of these strategies has been noted previously [7].

Literature

Industry 4.0, Factory of the Future, Smart Factory, Smart Production, Smart Manufacturing, Advanced Manufacturing and Digital Factory [8] are slogan expressions that refer to integrated low-cost automation/robotics, the Internet of things, and the acquisition, storage and intelligent exchange of digital data. Mobile devices such as smartphones, tablets, exoskeletons and various other portable technologies as well as Cyber-physical Systems (CPS), social media and networks are viewed as technologies that enable these integrated systems. While some pundits do not hesitate to proclaim an industrial revolution, others talk about a new phase of industrial digitization [9] extending throughout the value chain. We call the latter digital-organized production.

Several countries have taken this path of development to slow or reverse their de-industrialization and deal with their demographic challenges: Germany, the USA and China, to name only a few [2]. Canada is no exception: The Quebec aeronautical and manufacturing industries have embarked on this adventure, as announced at the Montreal summit on innovation in November of 2016. The Quebec government has published an action plan to support small to medium-sized enterprises (SMEs) in their transition towards a digitized economy [10].

Workers are and will remain a major and indeed indispensable resource in businesses [1,5,7,11-14]. Real-time control of the entire socio-technical system holds the promise of allowing workers to focus on value-adding activities (e.g. quality assurance) and to have greater autonomy on the job (decisional and workload management), better balancing of work with personal life, and in the case of older workers, longer work relationships [2,3,15-18]. For example, assembly decisions will have software support, and simulations of machine operation in interaction with humans will be integrated through real-time digital visualization [19,20]. The Internet of things and services, the web of things, big industrial data and smart data are game changers [1,2,12]. Some observers are forecasting that businesses will compile employee personal data including whereabouts, position, vital signs and work quality [2]. Digital-organized production is expected to lead to a new organization of work and open new possibilities for optimizing labor versatility: Dynamic and adaptive allocation of staff [7].

Staff allocation problems (also called job rotation problems) have been studied for decades using mathematical optimization or work sciences techniques and more recently approaches integrating both disciplines. The findings are of interest primarily in the services sector, such as the restaurant business, retail sales, public transport and health services, and in the manufacturing sector [21]. They deal with assigning tasks to workers and workers to stations and work shifts (including planning of hiring and lay-offs or dismissals), managing workers' use of time (e.g. providing pauses or breaks) or allotting vehicles, equipment and tools to workers [21]. Existing job rotation programs are focused primarily on managing biomechanical and organizational risks [6]. Analytical models focused on integrating these two perspectives include factors such as details of work contracts (work shifts, part-time, flexible scheduling), worker preferences, level of production, skills, training, physical capacity and experience, as well as the effects of learning [13,21-24], exposure to noise, physical workload or anthropometric data [13,22,23,25-29], age [11,14] and cognitive ergonomic factors such as human reliability or task complexity [27,30,31].

Published studies of dynamic and rational-analytical staff allotment policies that take human factors into consideration (the term 'personnel-integrated simulation' suggested previously [30] appears suitable) focus essentially on at least one of four principal approaches:

- Integrating variables from work sciences into existing process scheduling or balancing models via constraints in the model [21,32];
- Treating the staff allocation problem as a multi-criteria/objective decision problem [21,24];
- Building a model based on heuristics or meta-heuristics (artificial intelligence approaches) such as genetic algorithms, the simulated annealing algorithm or ant algorithm [22,25,28] fuzzy logic [27] or particle swarms [26] to integrate certain operational risks into risks identified in work science [6];
- Building a model based on integer (linear or nonlinear) programming [11,27,29,33,34].

Problem

Meta-heuristics can be used to solve complex problems [21] and are thus suitable in principle for the challenge of dynamic and adaptive allocation of staff. However, rarely have all factors under consideration been integrated into a single model [21,28] or has the uncertainty of the studied variables been taken into consideration [21]. It is also surprising that in spite of years of development; very few tools from work sciences are included in these models. Some of these, such as Methods Time Measurement (MTM) and Ergonomic Assessment Worksheets (EAWS) [35], have reached a significant technology readiness level. EAWS is an established tool [36] used to obtain answers to practical ergonomic questions regarding musculoskeletal load in factories while minimizing the effort to response precision ratio. It also provides helpful information for designing or re-designing workstations [37] and is compatible with human modeling software [38]. Digital Human Modeling (DHM) is used frequently in certain situations involving precision work [35]. High-quality software such as Safe Work has been commercialized. Nevertheless, in most work environments, much simpler and quicker solutions may be envisaged and preferred [39,40]. The use of multi-criteria models raises the difficult challenge of weighting the various criteria appropriately, which may be avoided by using artificial intelligence techniques such as the dominance-based rough set approach [41]. In several new models being proposed, Occupational Health and Safety (OHS) factors are considered statically, while workplace reality is dynamic and stochastic. Several major OHS factors are poorly supported or neglected, in particular those associated with cognitive workload and exposure to contaminants. Understanding of OHS risks to be integrated is at various levels of sophistication, suggesting that qualitative data as much as quantitative data need to be integrated. The integration of qualitative risks into any model requires expert elicitation. The literature is scant of details on how said experts are selected and on the protocol followed. The aim of several models is to reduce the cumulative exposure of workers to OHS risks, while an intervention at the source should be the priority. Finally, all these advances also raise significant issues regarding legality [2,13], ethics and safety [1,2,42].

Implications

The wish that emerges clearly in the documentation on Industry 4.0 is that human beings remain the focus of managerial preoccupations [2,3]. This has led to a development called personnel-oriented simulation [30,43], which raises the following question: How to generate a job rotation schedule that minimizes physical workload (e.g. considering posture, frequency of movements, exposure to biomechanical risks), cognitive workload (having implications for fatigue, error rate, accidents due to monotony or carrying out simultaneous tasks that can interfere with each other, superimposed cognitive demands or multi-sensorial solicitation) and exposure to noise or contaminants, is respectful of the skills, abilities, preferences or limitations (e.g. in the case of temporary assignment to a job) of workers in a crew, allows sufficient recuperation (suitable breaks or pauses), is coherent with organizational constraints (e.g. hourly rates or trade/professional exclusivities involved, the learning curve associated with a task) and improves the performance (e.g. processing/production time, profit margin, quality) of the production line or service? How does one structure and balance the work assigned to crews in such as context? How to schedule and coordinate the work of each member of these crews dynamically? These are the challenges to be met, keeping in mind that "there is, however, no 'one-size fits all' design of teamwork within a production system" [44].

Future

In several business sectors, continued success will rely on managerial interventions that are interdisciplinary and focused on human beings. Knowledge of the variety of spheres that intersect in OHS will have to be integrated dynamically and adaptively, for example by virtual analyses of analytical tasks or dynamic analyses of risks and safety. OHS must draw on smart technologies, in particular the most recent developments in portable biometry devices (e.g. ECG, pulse, respiratory volume and frequency) and real-time measurement of contaminants as well as virtual reality and simulators. Work sciences experts will have to become more at ease with artificial intelligence and develop, among other things, a dynamic and adaptive model of staff allocation that respects the principles of eliminating or reducing OHS risks at their source.

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