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Modelling human network behaviour using simulation and optimization tools: the need for hybridization

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Abstract

The inclusion of stakeholder behaviour in Operations Research / Industrial Engineering (OR/IE) models has gained much attention in recent years. Behavioural and cognitive traits of people and groups have been integrated in simulation models (mainly through agent-based approaches) as well as in optimization algorithms. However, especially the influence of relations between different actors in human networks is a broad and interdisciplinary topic that has not yet been fully investigated. This paper analyses, from an OR/IE point of view, the existing literature on behaviour-related factors in human networks. This review covers different application fields, including: supply chain management, public policies in emergency situations, and Internet-based human networks. The review reveals that the methodological approach of choice (either simulation or optimization) is highly dependent on the application area. However, an integrated approach combining simulation and optimization is rarely used. Thus, the paper proposes the hybridization of simulation with optimization as one of the best strategies to incorporate human behaviour in human networks and the resulting uncertainty, randomness, and dynamism in related OR/IE models.

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Keywords: Modelling human behaviour, human networks, simulation, optimization, simheuristics.

1 Introduction

Operations Research/Industrial Engineering (OR/IE) methods such as simulation and optimization are frequently employed in the design, development and optimization of complex networks and systems (Derigs, 2009). The realistic representation of these systems and networks through suitable models is hereby of major importance. Even

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though complex systems and networks from different application fields have been extensively studied by the OR/IE community, the consideration of realistic stakeholder behaviour in these models is not so usual (Crespo Pereira et al., 2011, Elkosantini, 2015, Neumann and Medbo, 2009). However, behavioural factors (either associated to isolated individuals or complete collective entities) are usually among the most important components in any real-life system. As such, simplifying behavioural assumptions neglecting the major impact of uncertainty, randomness, and dynamism that characterizes individual stakeholder behaviour often make OR/IE methods inapplicable in practice (Baines et al., 2004, Bendoly, Donohue and Schultz, 2006, Schultz, Schoenherr and Nembhard, 2010, Wang et al., 2015).

Nevertheless, the consideration of behavioural factors related to cognitive and social psychology is only one side of the coin. As individual agents are highly influenced by the contacts, ties, and connections shaping the group- and system dynamics of the human networks in which they operate, the modelling of human network interrelations is also of highest importance (Renfro, 2001, Russel and Norvig, 2003). Knoke and Yang (2008) even suggest that structural relations between different network actors follow the same patterns: (i) they are often more important in explaining behaviour than individual traits such as age, gender, etc.; (ii) they affect the perceptions, beliefs, and actions of individual network agents through structural mechanisms of human networks; and (iii) they are dynamic over time.

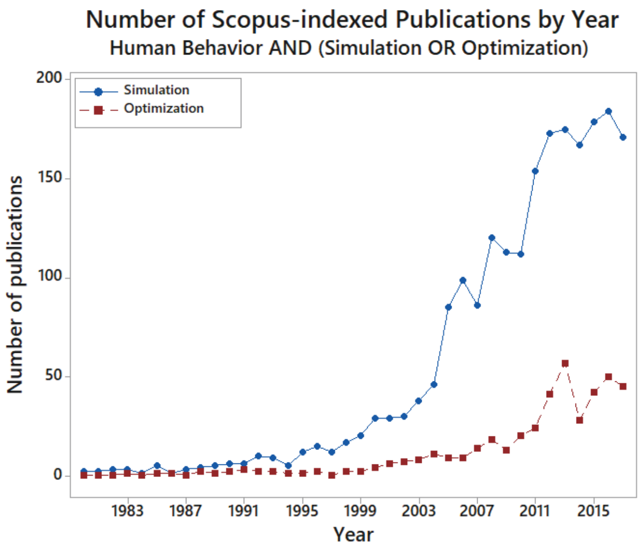

Figure 1: *Evolution of publications related to human behaviour in combination with simulation and/or optimization in Scopus indexed journals.*

The inclusion of human behaviour in simulation and optimization models has received increased attention in recent years. Figure 1 shows a clear increase in Scopus-indexed publications related to human behaviour in the context of simulation or optimization. Especially in the areas of computer science, engineering, and mathematics the incorporation of complex system dynamics through behavioural traits seems to be of interest (Figure 2).

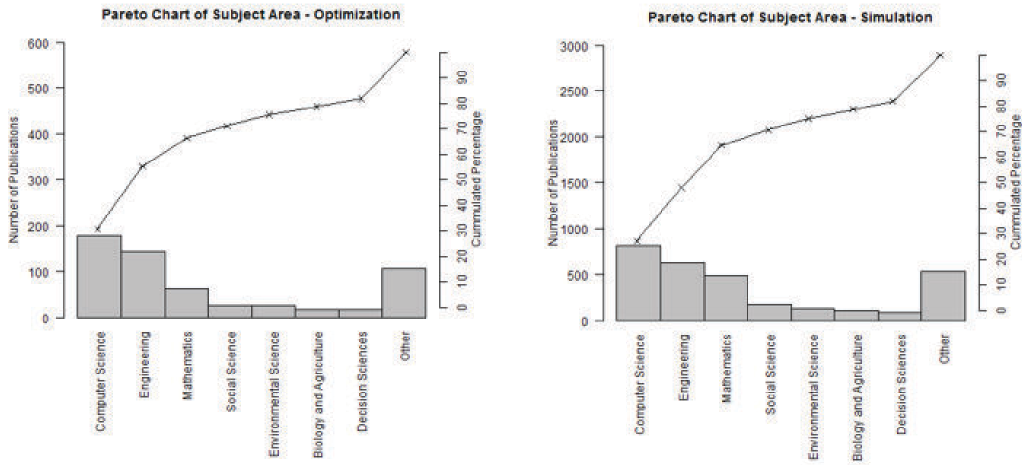

Figure 2: Subject area of publications related to human behaviour in combination with simulation and/or optimization in Scopus indexed journals.

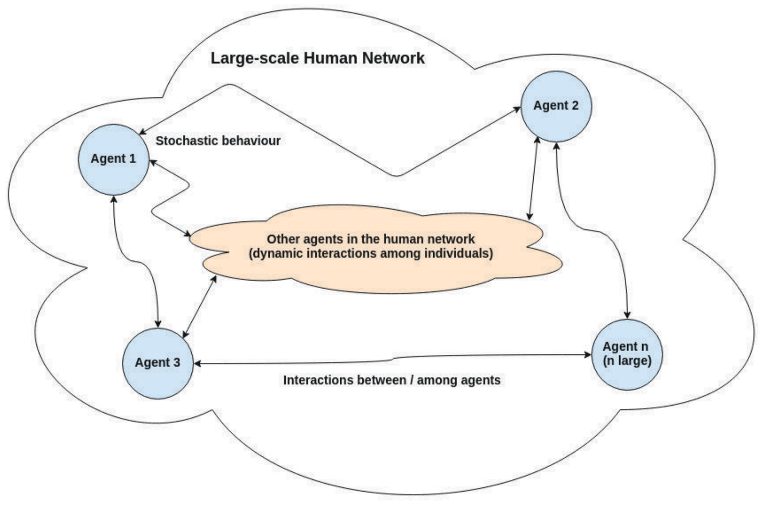

Figure 3: Representation of a multi-agent human network.

Simulation is mostly used to evaluate complex systems in which multiple actors interact in specific multi-agent human networks, similar to the one outlined in Figure 3. In this context, multi-agent systems (MAS) and agent-based modelling (ABM) arose with the desire to study complex and adaptive systems and their behaviours (Heath and Hill, 2010). Individual agents are thus modelled with unique attributes and behaviours, reacting to the actions, perceptions, and interrelations with other stakeholders in the mod-

Table 1: *Overview over reviewed human network environments.*

Human Network Environment	**Main Focus**
Supply Chain Management (Section 2)	**Manufacturing & Production** x Cooperation among workers x Workload balance and corporate social responsibility x Workers initiative and autonomy x Ergonomic conditions at work x Robustness of human network with increasing size **Logistics & Transportation** x Personal attitudes towards uncertainty in demands x Collaborative transportation management x Horizontal cooperation among carriers x Collaboration of urban freight stakeholders x Coordination in the use of shared parking spots
Public Policies in Emergency Situations (Section 3)	**Disease & Epidemics Dynamics** x Disease propagation and dynamics x Policies to limit the impact of fatal disease spreading x Infection control policies **Healthcare Emergencies** x Policies for an efficient patient care x Human resources allocation for managing patient overflow **Evacuations** x Perception of hazards in emergency situations x Efficient and real-time communication during evacuations x Navigation within social groups (crowd flow patterns) x Evacuation policies and procedures x Human interaction during evacuation of buildings x Movements of vehicles and pedestrians under emergencies x Detouring and avoiding congestion vs. greedy behaviour
Internet Social Networks (Section 4)	**Influential User Definition** x Viral marketing campaigns x Optimal display of advertising x Asymmetric influence relationships x Pricing policies **Community Establishment** x Discovery of network communities x True and false friend links x Degree of separation among users x Identification of market target groups **Other** x Trust-based relationships x Propagation of Internet-based human network viruses x Evolution of the network due to individual behaviour x Multi-agent rumor spread x Information propagation

elled system environment (Bandini, Manzoni and Vizzari, 2009, Kennedy, 2010, Macal and North, 2010, Siebers, Aickelin and Menachof, 2008). While ABM is the most common simulation approach to model behavioural traits in a human network environment, discrete event simulation (DES) has also been applied in to model resulting system dynamics (Robinson, 2014). However, this more process-oriented approach is less commonly applied to model agent behaviour and their impact on human networks (Siebers et al., 2010). DES frameworks for modelling social behaviour in networks are presented for example by Alt and Lieberman (2010) and Hou et al. (2013).

While simulation seems to be the natural way to incorporate human behaviour dynamics and the resulting randomness in the evaluation of human network structures, optimization is usually required to increase the efficiency of related processes. Resulting optimization problems are either addressed by exact solution methods for smaller instances, or approximate methods such as metaheuristics for larger problem settings (Talbi, 2006, Vazirani, 2012). Dynamic and uncertainty conditions are usually modelled using random variables in objective functions and constraints, e.g. through Monte Carlo simulation (MCS) or fuzzy logic.

This paper reviews existing work from the simulation and optimization fields in which human behaviour in human networks has been successfully modelled. Accordingly, the focus is put on three human network environments in which agent behaviour and stakeholder interrelations play a decisive role, namely supply chain management (SCM), the evaluation of public policies in emergency situations, and the structural analysis human network users in the Internet. Table 1 provides a more detailed overview over the discussed application fields. From this critical analysis of existing simulation and optimization models, a second contribution emerges: we provide arguments supporting the need for hybridizing simulation with optimization methods as a natural way to include human network behaviour in OR/IE models.

Accordingly, this work is structured as follows: Section 2 analyses the literature focusing on human behaviour in SCM. Section 3 discusses works on human behaviour in public policies in emergency situations. Section 4 is devoted to examine literature on human behaviour in Internet human networks. Hybrid simulation-optimization, as a natural way to include human network behaviour in optimization models, is closer discussed in Section 5. To conclude, Section 6 highlights the main contributions of this work.

2 Considering behavioural traits in supply chain networks

The efficient organization of material and information flows in SCM requires effective interaction and cooperation between different supply chain agents. To realistically model the resulting human network dynamics, different behavioural issues have to be addressed. In the following, Section 2.1 analyses existing literature concerning manufacturing & production processes in which human network dynamics (mainly through the interaction between individual employees) are considered. Later, behavioural aspects in the design and evaluation of logistics & transportation concepts such as collaborative transportation management or city logistics are reviewed in Section 2.2. An overview of the analysed papers and their OR/IE modelling approach to address human network behaviour is given in Table 2. Notice that many of these papers do not consider optimization.

2.1 Applications in Manufacturing & Production

The importance of considering human behaviour in manufacturing systems by integrating psychological and emotional aspects is stressed by Elkosantini and Gien (2009). In their work, they propose an agent-based simulation model to represent a production line including workers, whereby special attention is paid to individual behaviour and social relationships between workers. The authors highlight the influence of social interaction among employees on individual performance levels. Other OR/IE models in the context of manufacturing & production address individual human factors such as fatigue, motivation, education, or personalities (Digiesi et al., 2009, Elkosantini, 2015, Huerta, Fernandez and Koutanoglu, 2007, Khan, Jaber and Guirida, 2012, Riedel et al., 2009, Silva et al., 2013). Also in this context, Grosse et al. (2015) developed a framework that allows the integration of human-related factors into models associated with the planning of tasks.

Spier and Kempf (1995) were among the first authors in proposing the inclusion of human interrelations in simulation models. The authors use object-oriented simulation to test learning effects among workers in a small manufacturing line, showing that proactive and cooperative agents provide the best company performance. More recent work on similar issues apply ABM or DES to analyse, simulate, and evaluate production lines, workforce allocation in manufacturing cells, or the impact of engineers in the product design process. Okuda et al. (1999) stress that cooperation can be a key attribute in the planning of efficient production lines. The authors test different production process designs (e.g. U-shaped production lines and manufacturing cells) in terms of workload balance and total throughput in small-lot manufacturing, characterized by a high need for production flexibility. By using ABM, the impact of cooperation through human-oriented production lines is assessed. The paper concludes that production processes taking into account human behaviours (inter-worker learning effects) achieve the most balanced working times and the highest company output.

Various simulation models focusing on workforce allocation in production lines have been developed in the past. However, most of them do not consider the impact of human behaviour and collaboration in their models. Zhang et al. (2015) overcome this drawback by integrating different models of human agents in the context of a dynamic systems with a discrete-event behaviour, which they use to evaluate changeover processes in manufacturing processes. By modelling and simulating the dynamics of work process together with the dynamics of human behaviour, the authors show that the incorporation of different cooperation styles and skill levels can has a noticeable effect on the expected throughput of the system. From the reported simulation experiments, it can also be concluded that changeover assignments based on collaborative strategies lead to the best system performance.

The effects of collaborative product design processes (PDPs) are studied by Yang, Song and Zhang (2007). They argue that many simulation methods applied in the planning of efficient PDPs are too task oriented and do not represent the central role of designers in the process, which is deeply impacted by human initiative and autonomy, but also by collaboration within project teams. They elaborate an ABM to predict, manage, evaluate, and improve manufacturing design processes. Therefore, the design evaluation depends on the degree of cooperative behaviour among the product design team-members. Furthermore, human factors such as efficiency of designer and organization, human workload, error, and collaboration levels are taken into account. Another ABM to represent the dominant role of product designers in PDPs is proposed by Li, Zhang and Zhang (2011). The designer agents in their model have distinctive characteristics such as initiative, autonomy, and collaboration skills. They construct a simulation model of a motorcycle design project, allowing to analyse PDP traits such as organizational structure, scheduling strategies, and partner selection while considering individual and social behavioural traits.

ABM seems to be the predominant method of choice for modelling and simulating social interactions in manufacturing systems. However, there are some works that address the issue by using DES approaches. Crespo Pereira et al. (2011) propose a manufacturing DES environment that allows them to conduct training and research on how human operations take place. Their experimental system allows the consideration of human factors such as inter-group differences, worker experience, buffer capacities, work-sharing, and process state perception. Experimental results based on a real-life case show that inter-group variations, experience, and ergonomic conditions have a significant impact on the process outcome. Also using DES, Putnik et al. (2015) test the robustness of large production networks in environments with demand uncertainty. By modelling the behaviour of socially connected individuals, their work shows that system robustness and production rates depend on system sizes and human networks. According to their simulation experiments, large human networks with lots of business relations positively impact network robustness, while the production rate exhibits a nontrivial relation to the number of connections.

2.2 Applications in Logistics & Transportation

In the face of increasing market complexity driven by rapidly changing customer preferences, globalization, and fierce competition, the need for effective supply chain management (SCM) among suppliers, manufacturers, distributors, and retailers lead to complex dynamic systems. In response to this, many innovative planning models of logistics & transportation systems such as collaborative transportation management (CTM) or city logistics (CL) are based on the idea of stakeholder collaboration (Crainic, Ricciardi and Storchi, 2009, Taniguchi, Thompson and Yamada, 2012, Benjelloun and Crainic, 2009). Consequently, behavioural factors on an individual and network level have to be considered in the design of sustainable and integrated transportation & logistics structures (Geary, Disney and Towill, 2006, Sarimveis et al., 2008).

In the context of CTM, different simulation approaches have been used to include cognitive behaviour (e.g., individual thinking, deciding, and reasoning processes) and social factors (e.g., relationships and inter-organizational influences). As such, Yuan and Shon (2008) propose a CTM model based on the collaboration in transportation management among different supply chain partners. Their simulation tool is developed as realistic representation of a beer supply chain with four levels. The authors show that transportation costs and vehicle utilization levels can be significantly improved by collaboration and coordination of transportation activities. Chan and Zhang (2011) use Monte Carlo simulation (MCS) to evaluate benefits of CTM in long term relationships between retailers and carriers. The authors illustrate the concept of carrier flexibility to optimize delivery lead times. Their results show that collaboration between both parties can reduce retail costs while improving service levels. A conceptual framework for a behavioural multi-agent model considering the impact of cognitive and social behaviour is presented by Okdinawati, Simatupang and Sunitiyoso (2014). They propose the inclusion of Drama Theory (see Bryant (2003, 2004)) in their model. This allows the consideration of stakeholder behaviour in conflict and collaboration scenarios during the hierarchical decision making process of CTM strategies on an operational, tactical, and strategic level.

Using ABM, Li and Chan (2012) describe the impact of CTM on SCM with stochastic demands. They simulate a three-level supply chain while taking into account factors such as company characteristics, their types of action, and changes in company behaviour. By comparing the efficiency level reached in non-cooperative scenario with the cooperative case, the authors show that CTM can reduce global costs while increasing supply chain flexibility. Their work concludes that CTM is an efficient approach to tackle demand disruptions. Yu, Ting and Chen (2010) use DES to test different information sharing scenarios between supply chain members. More specifically, they consider information sharing about demand, inventories, capacities, and their different combinations. Their results suggest that especially information-sharing concerning customer demands is critical for supply chain success. Furthermore, they show that a full cooperative scenario based on shared information and assets is ideal for obtaining higher levels of efficiency in most supply chains. There are some metaheuristic approaches that address similar concepts (e.g. Horizontal Cooperation) in which interactions between network actors are highly important (Pérez-Bernabeu et al., 2015, Quintero-Araujo et al., 2019), but these optimization methods have not yet reached the same integration level of behavioural issues as simulation approaches.

Related to CL, Tamagawa, Taniguchi and Yamada (2010) develop a multi-agent methodology to evaluate different CL measures (road pricing, truck bans, motorway tolls) taking into account the behaviour of partners in urban freight transportation. More specifically, the modelled agents represent motorway operators, administrators, residents, shippers, and freight carriers. The authors develop an acceptable network environment for all stakeholders by considering conflicting objectives, transportation cost, profits, and environmental effects. To evaluate different road networks, they apply a genetic algorithm to calculate different routing options from the resulting vehicle routing problem (VRP), which has to consider time windows. Furthermore, a learning prototype affecting the behaviour of different agents is implemented. This paper extends a similar work of Taniguchi, Yamada and Okamoto (2007), in which the authors show that the implementation of road pricing can reduce pollution emissions but may increase freight shipment costs. To avoid such effects, cooperative freight transportation systems are proposed.

Teo, Taniguchi and Qureshi (2012) test government measures affecting urban road networks (e.g., road pricing for trucks) in an e-commerce delivery system. Their ABM considers the behaviour of major stakeholders in the transportation environment. In particular, they propose a reinforcement learning strategy for administrators to represent realistic agent behaviour. Furthermore, the resulting routing problem is optimized with an insertion heuristic. According to their outcomes, when the government administrator considers freight vehicle road pricing, truck emissions can be significantly reduced. A multi-agent approach to evaluate the financial and environmental impact of implementing urban distribution centres in urban areas is presented by Duin et al. (2011). The authors consider and test the dynamic behaviour among different CL stakeholders. Moreover, the impact of stakeholders' behaviour and actions towards city measures like tolls, operational subsidies, or time windows, and entry restrictions within city centres is evaluated. Experimental results suggest that the development of a positive business environment for urban freight consolidation centres depends not only on physical factors such as traffic congestion, but also on the actions and behaviour of each system agent. Their ABM also incorporates a genetic algorithm for routing optimization.

Joint delivery systems, urban distribution centres, and car parking management within city centres are the CL measures analysed by Wangapisit et al. (2014). The focus of this study lies on the interaction and cooperation among urban freight stakeholders when CL measures are implemented. The authors use ABM combined with reinforcement learning and an insertion heuristic to solve extended VRP versions with pick-up-and-delivery and time windows. Their results suggest that urban distribution centres and joint delivery systems can improve the environmental impact of urban freight transportation. They fine-tune the distribution centre implementation by applying urban parking management and subsidies for shopping street associations. Car parking management in an ABM is also the matter of research in the paper by Boussier et al. (2009). Their simulation models considers the behaviour of different agents, focusing of shared parking spaces between private and commercial vehicles. Furthermore, the use of electric vehicle fleets in the development of 'greener' transportation systems is taken into account in some works (Juan et al., 2016, Eskandarpour et al., 2019).

Table 2: Summary of reviewed papers related to Supply Chain Management.

Area	Paper	Simulation			Optimization
		ABM	DES	Other	(Meta-) Heuristics
Manufacturing & Production	Spier and Kempf (1995)			x	
	Okuda et al. (1999)	x			
	Yang et al. (2007)	x			
	Li et al. (2011)	x			
	Crespo Pereira et al. (2011)		x		
	Zhang et al. (2015)	x			
	Putnik et al. (2015)		x		
Logistics & Transportation	Taniguchi et al. (2007)	x			x
	Yuan and Shon (2008)			x	
	Boussier et al. (2009)	x			
	Yu et al. (2010)		x		
	Tamagawa et al. (2010)	x			x
	Chan and Zhang (2011)			x	
	Li and Chan (2012)	x			
	Teo et al. (2012)	x			x
	van Duin et al. (2012)	x			x
	Wangapisit et al. (2014)	x			x
	Okdinawati et al. (2014)	x			

3 The impact of public policies on human networks behaviour in emergency situations

This section reviews different approaches in which human network behaviour in emergency situations is addressed. In this field, especially the reaction of complete population groups to public policies in the face of disease and epidemic dynamics (Section 3.1), other healthcare emergencies (Section 3.2), and evacuation situations (Section 3.3), has recently been a topic of interest. Table 3 summarizes the reviewed works.

3.1 Applications in Disease & Epidemics dynamics

Human behaviour in human networks has a strong influence on how civil infrastructures are used. Thus, whenever public polices have to be designed these human factor should be considered. Likewise, social interactions provide an ideal environment in which diseases can easily be spread out. For those reasons, social interactions need to be considered when designing public policies, since the behaviour of citizens in response to these policies as well as their reaction to situations of crisis can modify the usual social patterns.

The most remarkable papers in the literature regarding simulation of these issues use ABM simulation. Thus, related to policy making in large-scale networks, Kasaie and Kelton (2013) consider the problem of resource allocation in the control of epidemics. They assume a fixed budget to be allocated among competing healthcare interventions, with the goal of achieving the best health benefits. Interventions thus include vaccination, prevention, or treatment programs. Their constructed ABM is combined with a response surface methodology as sequential optimization technique for the resulting resource allocation problem, depending on different investment strategies.

Considering realistic and large-scale human networks, Bisset et al. (2009) analyse the evolution of human behaviour and disease dynamics. These authors use a highly detailed interaction-based simulator to simulate sixteen scenarios, established by combining different types of intervention policies during the spreading of fatal diseases: closure and reopening of schools, quarantine policies, and vaccinations policies. Published results indicate that quarantine and other isolation polices seem to have a limited impact on the overall rate of infection. Also, individual isolation policies are typically employed at late stages of the epidemic outspread, which in practice limits their effectiveness. Other isolation policies (e.g, quarantine of some individuals) tend to affect only a small portion of the total population, which also limits their efficiency. However, a combination of vaccinations and quarantine policies seems to be effective since the number of key citizens infected is reduced. Concerning school closures, the results suggest that even very low levels ($<0.1\%$) of residual infection rates among pupils can cause new infection waves after disease epidemics.

Focusing on a smaller and enclosed area, Laskowski et al. (2011) proposed a model to study, by means of simulation, the spread of influenza virus infections in the emergency department of a Canadian hospital. Their simulation used a set of patients and healthcare workers, modelling their individual properties as well as their social interactions. According to their results, those policies oriented to controlling the infection in patients (e.g., masking symptomatic patients or alternate treatment streams) are usually more efficient than those other policies focused just on healthcare workers.

3.2 Applications in Healthcare Emergencies

Effective management of Emergency Departments (ED) is an important problem in healthcare systems. The frequency of arrival of patients, the waiting time of patients, the treatment given, the emotions of the doctor, the nurse management of patients, etc. are factors that affects the quality of ED. Overcrowding and high flow in ED will have higher probability of conflict occurrence. Conflict happens in every ED, so a good policy is needed to confront the crowded situation in order to maintain the quality of ED. The analysis of this particular human network behaviour play a key role in developing policies and decision tools for overall performance improvement of the system. The ability to accurately represent, simulate and predict performance of ED is invaluable for decision makers.

Brailsford (2016) develop a review on simulation models for healthcare applications in which the simulated objects (entities) are human beings. This study focuses specifically on whether it is desirable (and possible) to incorporate human behaviour within the conceptual design of a simulation model. However, the reality is that, although there are many approaches in the literature dealing with healthcare emergencies through simulation (Almagooshi, 2015), only a few of them consider human network behaviour and optimization. Thus, Rico, Salari and Centeno (2007) study the best nurse allocation policy to manage patient overflow during a pandemic influenza outbreak. Their approach combines DES with OptQuest - an optimization software that includes metaheuristics, exact methods and neural networks - in order to analyse different configurations regarding the number of nurses needed for healthcare delivery. Some other works in the literature apply the same combination of a DES model and OptQuest including human network behaviour in healthcare emergencies. Thus, Silva and Pinto (2010) evaluate the performance of a medical emergency system creating a simulation model and using optimization to analyse different scenarios and find the best parameters for it. Similarly, Weng et al. (2011) use this combination to optimize the allocation of human resources in a hospital emergency department. With a different methodology, Liu (2017) analyse a complex Spanish ED and provide an ABM simulation considering patient arrivals based on historical data. The interaction between doctors, nurses, technicians, receptionists, and patients is studied and modelled. Additionally, some optimization methodology is used for calibrating model parameters under data scarcity.

3.3 Applications in Evacuation Situations

The perception of risk during emergency evacuations can generate stress on the population, which can derive in selfish and unorganized behaviours driven by the survival instinct (for example, by blocking narrow evacuation exits). This seriously effects survival rates and the evacuation efficiency levels. In this context, the analysis of human behaviour during emergency situations contributes to build efficient emergency management plans. As such, Parikh et al. (2013) note the importance of communication in such events. Their ABM considers population behaviour and its interaction with various interdependent infrastructures, in order to develop efficient evacuation plans considering a nuclear detonation. Their results stress the key role of agent communication, as it can beneficially alter human behaviour in the evacuation phase by reducing crowd panic and increase mobility levels.

Chu et al. (2015a) propose an agent-based simulation tool that is able to consider both human and social behaviours previously analysed in scientific works related to management of disaster and safety situations. They use several approaches to model the behaviour of each agent: (i) the user follows exits that are familiar to her; (ii) the user follows cues from building features; (iii) the user will navigate within a group of related people; (iv) and the user will follow the crowd. As expected, their simulation results show that the flow patterns might be greatly influenced by the specific arrangement of exit signs, knowledge of the environment, and even social settings. Thus, these authors are able to pinpoint and evaluate the effect of social features on flow patterns. Their analysis provides insights concerning architecture, building layouts, and facility management in the design of user-centric facilities, emergency procedures, and related training programs. Later, the authors applied the same simulation tool to examine egress performance of a museum (Chu et al., 2015b). Their simulation considers different scenarios of people and group behaviour in emergency situations. Their approach allows a closer analysis of museum visitors in emergency situations to improve the design of safe egress systems and procedures.

Similarly, to represent an evacuation situation Chu and Law (2013) propose an agent-based simulation study in which social behaviour is considered. Agents are represented considering the incorporation of behavioural rules on an individual, group, and crowd level. Results reveal that social behaviour during evacuation processes can affect the overall egress time and pattern. In a model combining human behaviour with buildings, Liu et al. (2016) study the dynamic effect of damaged structures on the evacuation of buildings. Their agent-based model hybridizes probabilistic components with finite-element theory to analyse how people interact during the evacuation process. The reported simulation results show that the evacuation time can suffer a noticeable increment when considering the grouping behaviour.

Table 3: *Summary reviewed papers related to public policies in emergency situations.*

Area	Paper	Simulation			Optimization		
		ABM	**DES**	**Other**	**Exact & Approximation Methods**	**(Meta-) Heuristics**	**Other**
Dynamics of Diseases & Epidemics	Bisset et al. (2009)			x			
	Laskowski et al. (2011)	x					
	Kasaie and Kelton (2013)	x			x		
Healthcare Emergencies	Rico et al. (2007)		x				x
	Silva and Pinto (2010)		x				x
	Weng et al. (2011)		x				x
	Liu (2017)	x					x
Evacuations	Kagaya et al. (2005)	x					
	Zhang et al. (2009)	x					
	Song et al. (2010)	x					
	Luh et al. (2012)	x				x	
	Chu and Law (2013)	x					
	Parikh et al. (2013)	x					
	Chu et al. (2015a)	x					
	Chu et al. (2015b)	x					
	Fu et al. (2015)			x			
	Liu et al. (2016)	x					

Unlike the studies mentioned above, Luh et al. (2012) make an effort to integrate optimization techniques into their model. In order to do so, these authors use a macroscopic network-flow model. Their model takes into account different factors related to the desire of escaping, such as smoke, fire, and even psychological ones. Thus, they employ stochastic dynamic programming to optimize escape routes for both groups and individuals. To reduce the impact of limited passage capacities on the evacuation flow, these routes are also coordinated in their model. According to the reported results, their approach is able to reduce evacuation time by diminishing bottlenecks through the path.

Next to the evacuation of people from buildings and facilities, human behaviour in human networks concerning traffic management play an important role when people are forced to leave whole areas, such as villages or cities. In particular, human behaviour might be influenced by different circumstances: *(i)* people tend to focus mainly on the prevailing situation instead of long-term interests; *(ii)* the availability and quality of traffic information might have a strong impact on human behaviour, including the choice of the escaping route; and *(iii)* instructions on evacuation paths might also affect the selection of the evacuation route. The route choice behaviour during evacuation processes is formulated by Fu et al. (2015) as a combination of the instructed route and the own user's perception on the time it might take to complete it. Thus, to model the user's behaviour a logit model and fuzzy set theory is used. According to the results provided by a simulation, there is a nonlinear impact of traffic data on the efficiency of the evacuation flow. Also, whenever real-time traffic data is available online, users are able to adapt their chosen paths, thus reducing the associated egressing times. Furthermore, a strong compliance enforcement concerning policy instructions contributes to higher evacuation efficiency.

Another urban emergency transportation simulation system is presented by Song, Yang and Du (2010). Their system is based on the Beijing metropolitan area with the focus of simulating vehicle and pedestrian movements in emergency situations. Results demonstrate the effectiveness of this system for producing evacuation routing strategies, optimizing emergency resources, identifying total evacuation times, and evaluating the performance of the whole operation. Similarly, Zhang, Chan and Ukkusuri (2009) address human interaction during evacuation processes. They use greedy agents that use a probabilistic rule and take into account the dynamic conditions of the network to select between the shortest path and the least congested one. By detouring and avoiding congested roads, some agents might be able to diminish their individual egressing times. However, this greedy behaviour also tends to increase the total time employed by all the agents to evacuate the system. Considering hazards caused by earthquakes, Kagaya et al. (2005) build the reproduction of human traffic behaviour and considering agent interaction. They classify evacuation behaviour into various patterns, which they then use to establish different rules concerning evacuation behaviour.

4 User behaviour in Internet-based human networks

The growing use of Internet-based human networks increasingly influences individual and collective conduct of people (Jin et al., 2013). Especially in the context of defining influential users and communities – for example, related to internet security and online marketing – structural network analysis using network and graph theories has received much attention. Social factors are implicit in this application area. For this reason, OR/IE problems related to the analysis of Internet-based human networks are a direct consequence of human networks and their dynamic behaviours. In contrast to previous application areas, where social factors should to be taken into account because of their influence on particular situations, problems discussed in this Section can be seen as direct consequence of human network behaviour among users. In more detail, Section 4.1 deals with research on individual network users. Then, Section 4.2 reviews papers in which network community structures are defined and analysed using OR/IE approaches. Furthermore, other related works are discussed in Section 4.3. Table 4 summarizes the works discussed in this section. Notice again that column DES is not included in this table, since none of the approaches use it.

4.1 Identifying influential network users

Internet-based human networks are becoming more important for companies in the context of efficient and productive viral marketing campaigns. The influence maximization problem in Internet-based human networks was proposed by Domingos & Richardson (Domingos and Richardson, 2001, Richardson and Domingos, 2002). When modelling the Internet-based human network on a graph, the goal is to find a subset of nodes with the highest influence on the rest of the network. As shown in Figure 4, some individuals (nodes) might be more ‘influential’ than others, meaning that they have a larger number of connections (i.e., their opinions or actions might reach a large number of individuals). Also, not all connections are symmetrical: while some agents might be very influential over their contacts, the opposite is not always true. Heuristics are proposed as a tool to decide upon the most influential customers in the network. The idea is to focus marketing activities on customers with a high network value, instead of only considering the related expected intrinsic (direct) marketing value of each network member.

Kempe, Kleinberg and Tardos (2003, 2005) develop probabilistic rules based on findings from sociology and economics, which they embed into a decreasing cascade- and linear threshold model. They use greedy approximation algorithms to achieve influence maximization. The proposed greedy algorithms were later improved by Chen, Wang and Yang (2009). These authors also discuss an efficient degree discount heuristic, which is able to reach similar influence spreading results in substantially decreased calculation times. Considering a probabilistic voter model, Even-Dar and Shapira (2007) analyse the spread maximization problem. For that, they elaborate simple and efficient algo-

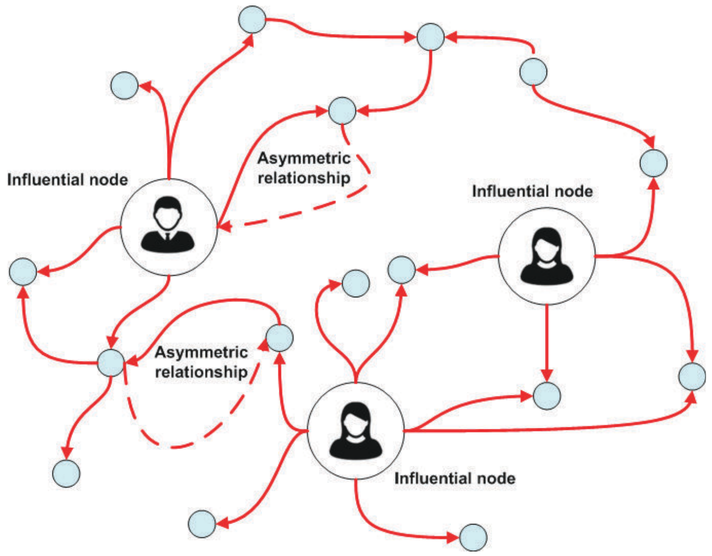

Figure 4: *Internet-based human network with influential nodes and asymmetric relationships.*

rithms. Kimura et al. (2010) later introduced an approach based on graph theory and bond percolation to reduce algorithmic computation times.

Some studies deal with the problem by considering competitive diffusion. Carnes et al. (2007) employ viral marketing to introduce a new product when a competing one already exists in the market. They assume that if an influential user chooses one product over another, then the members of his/her Internet-based human network will tend to do the same. These authors propose an approximation algorithm that is able to reach 63% of the optimal value. Later, Borodin, Filmus and Oren (2010) discussed a similar competitive environment, introducing a different approach to the original greedy one. Also, taking into account display advertising, the influence maximization problem has been explored by Abbassi, Bhaskara and Misra (2015). Here, online advertisement is shown to a pre-defined number of users. In order to find the optimal display strategy, these authors introduce alternative optimization heuristics. After completing a MCS study, their results show that especially a two-stage algorithm inspired by influence-and-exploit strategies yields promising results.

Most of the reviewed papers consider that social relationships can be modelled using undirected graphs (i.e., they are symmetric). However, trust and other social relationships might need to be modelled using directed graphs (i.e., they might be asymmetric or even unilateral). Xu et al. (2012) model the Internet-based human network on a directed graph including asymmetric influence relationships. In order to find a subset of users that have the highest influence in the network, they propose a mathematical programming approach. This is empirically evaluated using real-life data from Internet-based human networking sites. Ahmed and Ezeife (2013) develop a diffusion model that considers positive and negative trust influences in Internet-based human networks.

Influential nodes are identified with a local search based algorithm, which outperforms greedy approximation methods by as much as 35%.

The network influence effect is also considered in combination with the optimal pricing problem, in which different pricing policies are considered in the diffusion of a product. Considering a monopolistic market setting, Candogan, Bimpikis and Ozdaglar (2010) consider different scenarios concerning pricing policies (uniform, two-fold, and individual prices for the customers in the network) for a divisible good. Considering these scenarios, the authors propose an approximation algorithm for finding the optimal set of agents. Chen et al. (2010) propose an analogous concept. By taking into account incomplete information, these authors are able to extend the original model. Also related to this, a multi-stage pricing model is introduced by Hartline, Mirrokni and Sundararajan (2008). In this model, different price levels are set, at each different stage, by the manager. This work was later improved by Akhlaghpour et al. (2010) to include imperfect information of the considered agents.

4.2 Community discovery and structural analysis

Apart from identifying key network members and their influence on the behaviour of related nodes, another major research field concerning internet human networks is related to the detection of clusters and communities to structurally analyse large networks. In their comparison of network detection methods (i.e., approximation and heuristic algorithms), the concept of 'network community' is defined by Leskovec, Lang and Mahoney (2010) as "a group of nodes with more and/or better interactions amongst its members than between its members and the remainder of the network". The goal is to define such communities to study their behaviour over time. The authors name different approaches to identify network clusters. Principal component analysis are used in spectral algorithms to find communities (Kannan, Vempala and Vetta, 2004). Likewise, algorithms based on network flow represent edges by means of pipes with unitary capacity, and then are able to find communities by employing algorithms such as the max flow-min cut one (Flake, Tarjan and Tsioutsiouliklis, 2003). Other authors count the number of edges pointing inside and outside a giving community (Flake, Lawrence and Giles, 2000, Radicchi et al., 2004), which allows them to identify clusters in the network. Other works are concerned with maximizing the modularity of the identified communities (Girvan and Newman, 2002, Newman and Girvan, 2004).

Addressing the problem of maximizing modularity, Nascimento and Pitsoulis (2013) propose the use of a GRASP metaheuristic combined with path relinking. In other related work especially the use of memetic- and bio-inspired algorithms seem to be a major trend in recent years. Chen and Qiu (2013) introduce a novel particle swarm optimization algorithm, showing through synthetic and real-world networks that it can effectively extract the intrinsic community structures. Other particle swarm optimization algorithms have been applied in the same context by several works (Cai et al., 2014, 2015, Biswas et al., 2015). Ant colony optimization (ACO) has been applied by Sercan, Sima and Sule (2009) in mapping network-cliques to graph nodes. The resulting graph is then analysed using clustering based algorithms. Additional publications applying ACO algorithms to discover network communities include (Javadi et al., 2014, Jin et al., 2011, 2012, Mandala et al., 2013, Xu, Chen and Zou, 2013, Zhou et al., 2015). Further bio-inspired metaheuristics, such as artificial bee colony optimization algorithms, have also been used to deal with the problem (Abu Naser and Alshattnawi, 2014). Finally, also memetic or hybrid algorithms have been proposed in this context, e.g.: crossover operators combined with local search procedures (Gach and Hao, 2012), or a particle swarm optimization-based global search operator and tabu local search operator (Zhang et al., 2016).

Related as well to network community research and their structural analysis, in human networks over the Internet Huang, Lin and Wu (2011) propose an exact- and heuristic algorithm to define links that are either true- or false-friend ones. Other works are interested in identifying the degree of separation between two users. For instance, Bakhshandeh et al. (2011) present new heuristic search techniques to provide optimal or near-optimal solutions. Finally, Rivero et al. (2011) elaborated a metaheuristic algorithm based on ACO to perform the path search between two nodes in a graph. This algorithm outperforms other ACO algorithms when considering large-scale networks.

4.3 Other Internet-based human network analysis

Next to the definition of influential users and analysis of community structures in Internet-based human networks, other related topics can be defined in the discussed context. Zhang et al. (2008) and Ben-Zwi et al. (2009) determine marketing target groups – the set of users with the highest influence on their network acquaintances – by studying the trust relationships between customers in virtual communities. On the one hand, this problem is not exactly the same as the influence maximization one, since the objective is not to arrive to a higher number of nodes, but to identify node clusters with high trust levels. On the other hand, it is also different from the community discovery problem, since it is not based on network connectivity, but rather on trust-based relationships, making traditional clustering algorithms inapplicable in this kind of scenario.

Wen et al. (2013) use numerical simulation for their susceptible-infectious-immunized model, which allows them to analyse worm propagation in Internet-based human networks. In a similar approach, Singh and Singh (2012) study the inoculation of a certain fraction of nodes against rumors. For the modelling of specific agent behaviour in particular situations (e.g., when studying the evolution of the network as a result of personal member attributes and behaviours), numerical approaches are unsuitable, usually making ABM the preferred method of choice. Blanco-Moreno, Fuentes-Fernández and Pavón (2011) make use of agent-based simulation to analyse Internet-based human networks. Their framework allows the study of scenarios in which network members are modelled by characterized agents. These agents are customized taking into account other individuals, environmental conditions, groups, and the status of the entire net-

Table 4: *Summary of reviewed papers related to Internet human networks.*

Area	Paper	Simulation		Optimization	
		ABM	**Other**	**Exact & Approximation Methods**	**(Meta-) Heuristics**
Influence of Individual Network Users	Domingos and Richardson (2001)				x
	Richardson and Domingos (2002)				x
	Kempe et al. (2003)			x	
	Kempe et al. (2005)			x	
	Even-Dar and Shapira (2007)			x	
	Carnes et al. (2007)			x	
	Hartline et al. (2008)			x	
	Chen et al. (2009)			x	x
	Kimura et al. (2010)			x	
	Borodin et al. (2010)			x	
	Candogan et al. (2010)			x	
	Chen et al. (2010)			x	
	Akhlaghpour et al. (2010)			x	
	Xu et al. (2012)			x	
	Ahmed and Ezeife (2013)				x
	Abbassi et al. (2015)		x		x
Analysis of Network Community Structures	Shi et al. (2009)				x
	Sercan et al. (2009)				x
	Jin et al. (2011)				x
	Huang et al. (2011)			x	x
	Bakhshandeh et al. (2011)				x
	Rivero et al. (2011)				x
	Jin et al. (2012)				x
	Jin et al. (2011)				x
	Gach and Hao (2012)				x
	Nascimento and Pitsoulis (2013)				x
	Chen and Qiu (2013)				x
	Mandala et al. (2013)				x
	Chang et al. (2013)				x
	Xu et al. (2013)				x
	Qu (2014)				x
	Cai et al. (2014)				x
	Javadi et al. (2014)				x
	Abu Naser and Alshattnawi (2014)				x
	Biswas et al. (2015)				x
	Cai et al. (2015)				x
	Zhou et al. (2015)				x
	Zhang et al. (2016)				x
Other related Papers	Zhang et al. (2008)				x
	Ben-Zwi et al. (2009)			x	
	Blanco-Moreno et al. (2011)	x			
	Xiao and Yu (2011)	x			
	Singh and Singh (2012)		x		
	Sabater and Sierra (2002)	x			
	Kannabe et al. (2012)	x			x
	Wen et al. (2013)		x		

work. Notice that the use of agent-based simulation helps to develop more realistic models as well as to understand how the networks perform from the interactions among their nodes. Xiao and Yu (2011) develop a multi-agent rumor spread model in virtual communities. Different simulation tests are conducted to show the impact of network structures, rumor tolerance frequency, and the user's believing rate. Also using ABM, Sabater and Sierra (2002) propose a model based on the user's reputation, which contributes to enhance its level of representativeness as regards as certain networks.

Finally, Kannabe et al. (2012) constitute an excellent example of a hybrid approach combining metaheuristics with simulation (ABMS). These authors develop a propagation model to analyse how information spread in a Internet-based human network, thus affecting human behaviour. According to their outcomes, the effects of this propagation varies from homogeneous networks (those in which agents share similar characteristics) to heterogeneous ones.

5 Need for an integrated simulation-optimization approach

The literature review completed in the previous sections shows that the choice of the appropriate OR/IE methodology is highly context dependent. It seems that in some application areas (especially Manufacturing & Production and public policies in emergency situations), individual and network behaviour is mainly considered within the simulation community, whereas optimization tools are often applied in the design and evaluation of Internet human networks. However, in all discussed application areas it is necessary to account for the uncertainty associated with individual behaviour And the system dynamics that characterize complex network interactions when modelling behavioural traits.

Simulation techniques seem to offer a natural and efficient way to model both uncertainty and system dynamics over time. In particular, ABM has been successfully applied in a myriad of different application fields. Simulation itself, however, is not an optimization tool. Thus, whenever the problem at hand requires maximization or minimization of a given objective function (or several ones in the case of multi-objective optimization), simulation alone is not enough. A logical way to proceed in those cases is to combine simulation with optimization techniques.

As pointed out by Figueira and Almada-Lobo (2014), 'sim-opt' methods are designed to combine the best of both worlds in order to face: (i) optimization problems with stochastic components; and (ii) simulation models with optimization requirements. A discussion on how random search can be incorporated in simulation-optimization approaches is provided by Andradóttir (2006), while reviews and tutorials on simulation-optimization can be found in Fu, Glover and April (2005), Chau et al. (2014), and Jian and Henderson (2015). Since most human networks tend to be large-scale, the integration of simulation with metaheuristics (i.e., simheuristics) might become an effective way to include human factors inside *NP-hard* combinatorial optimization problems. Juan et al. (2018) provides a complete review of simheuristics (combination of simulation with metaheuristics), which facilitates to account for uncertainty in this kind of OR/IE problems. As discussed in Ferone et al. (2018), simheuristics allow for extendng traditional metaheuristic frameworks to solve large-scale complex problems with stochastic components, from transportation (Gonzalez-Martin et al., 2018) to telecommunication systems (Cabrera et al., 2014).

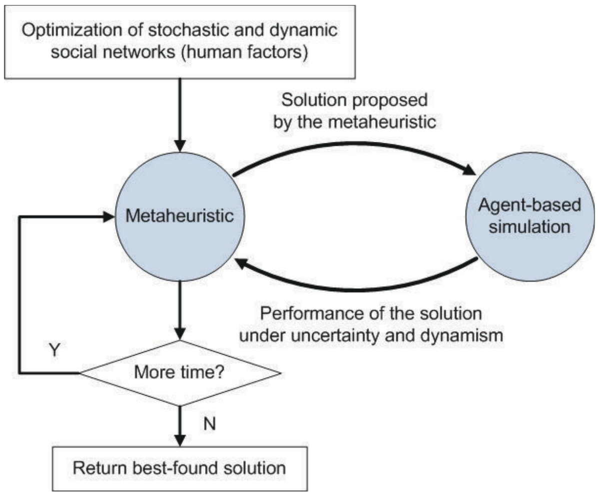

Figure 5: *Agent-based simheuristic framework.*

Accordingly, an open research line in modelling human factors inside large-scale human networks is the one related to exploring the fundamentals and potential applications of agent-based simheuristics (Panadero et al., 2018), where metaheuristic-driven algorithms make use of ABM to account for the uncertainty and dynamism present in these networks. As depicted in Figure 5, given an optimization problem involving human factors in human networks (i.e., a stochastic and dynamic large-scale system), the metaheuristic algorithm acts as an engine which proposes ‘promising’ solutions (one at a time) to the ABM module. Each of these solutions is then analysed by the ABM component, which provides estimates on the real performance of the proposed solution under the uncertainty and dynamic conditions associated with human factors. The feedback from the ABM module is used by the metaheuristic to guide the search process. This iterative process continues until a time-related ending condition is met. At that point, the best-found solution (or, alternatively, a set of top solutions with different properties) is offered to the decision maker.

Yet another interesting research area in this direction is that of ‘learnheuristics’ (Calvet et al., 2017), where metaheuristics are combined with machine learning in order to address variations in human behaviour due to changes in the environmental conditions. Thus, for instance, Calvet et al. (2016) propose a hybrid approach combining metaheuristics with statistical learning in order to account for variations in the willingness to spend of consumers as the ‘best-fit’ shopping centres have been already assigned to other costumers.

6 Conclusions

This paper reviews how human behaviour in human networks is included in two of the most popular OR/IE techniques: simulation and optimization. The paper comprises an extended survey of related works in different types of human networks: supply chain management, public policies in emergency situations, and Internet-based human networks. Based on the literature review, different techniques typically employed to model human behaviour and social interactions are identified. Furthermore, the main research issues when modelling behavioural traits are depicted, including: cooperation among workers, workload balance, workers’ initiative and autonomy, ergonomic conditions at work, personal attitudes, horizontal cooperation among carriers, disease propagation and dynamics, efficient and real-time communication during evacuations, crowd flow patterns, human interaction during evacuation of buildings, movements of vehicles and pedestrians under emergencies, viral marketing campaigns, pricing policies, discovery of network communities, identification of market target groups, information propagation, etc. Likewise, the pros and cons of each modelling technique have been highlighted. Thus, while agent-based simulation is the preferred methodology to modelling network systems dynamics and uncertainty, it is not a valid tool for optimization purposes. At the same time, metaheuristics are well suited to optimize large-scale human networks. However, they show severe limitations when human factors need to be fully considered. Accordingly, the paper argues in favour of hybridizing both techniques. One of these combinations is the so called ‘agent-based simheuristics’ approach. This integrated methodology benefits from the extraordinary capacity of metaheuristics to generate ‘promising’ solutions to large-scale combinatorial optimization problems. At the same time, stochastic and dynamic conditions that characterize human behaviour and social interaction can also be taken into account without compromising the resolvability of the corresponding optimization problem.

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