### AN AGENT-BASED MODELLING AND SIMULATION FRAMEWORK TO ASSESS SMALL BUSINESSES' RECOVERY FROM FLOODING

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### **ABSTRACT**

Small and Medium Enterprises (SMEs) form a major part of the economy in many developed countries. For example, in the United Kingdom, SMEs make up 99.9% of all businesses, and thus any disruptions to their operations, such as those caused by flooding, can have severe economic consequences. Given the importance of SMEs, research needs to be undertaken in modelling their behaviour when faced with operational disruptions due to flooding. Agent-Based Modelling and Simulation (ABMS) has been recognized as one approach that allows the study of complex problems in business. This paper outlines initial research carried out towards the development of an ABMS framework aimed at facilitating assessments of the effects of SMEs' behaviours on recovery from flooding.

Keywords: Small and Medium Enterprises; agent-based modelling and simulation; flooding; business recovery.

### 1. INTRODUCTION

Flooding can result in significant financial losses to a nation's economy due to the disruption caused to individuals, organizations and communities (Coates et al. 2014). In the United Kingdom (UK), Small and Medium Enterprises (SMEs) are essential to the economy as they account for 5.4 million businesses, which represents 99.9% of all businesses with the remaining 0.1% being large businesses (Rhodes 2015). However, the definition of what constitutes an SME varies depending on the country of origin (Hallberg 1999). For example, in the UK, the term SME refers to any business that has fewer than 250 employees (Lukács 2005), whereas in the USA and Australia it is fewer than 500 and 100 respectively (Ayyagari et a. 2007). In relation to the UK definition, SMEs are categorized as micro, small or medium according to their number of employees. That is, a micro-business has 1 to 9 employees, a small business has 10 to 49, and a medium business has 50 to 249 (White 2016). In recognizing the economic importance of SMEs, it has been seen in recent years that these businesses can be vulnerable to the effects of extreme weather events (Crichton 2006, Ingirige et al. 2010). This vulnerability has been reported as being due to their limited resources (Sullivan-Taylor and Branicki 2011, Van Gils 2005) and their tendency to lack disaster mitigation plans (Jones and Ingirige 2008, Li et al. 2015). Flooding, in particular, has caused significant financial losses to SMEs in the UK and remains a serious threat (Wedawatta 2013). According to the Environment Agency (EA), UK businesses' losses due to flooding in 2007 were estimated to be in the region of £740 million (Chatterton et al. 2010). In England, it is projected that the annual loss suffered by residential and business properties due to flooding is over £1 billion (Leinster 2009). Thus, mitigating the potential risk and disruption caused to SMEs by flooding has become an issue of key significance (Wedawatta and Ingirige 2012).

SMEs' preparation for, response to and recovery from disruptive events, such as flooding, depend on a myriad of complex and interdependent processes (Wedawatta 2013). ABMS is recognized as an effective tool for solving complex problems in business and social sciences (Prasad and Chartier 1999; Gilbert and Terna 2000; North and Macal 2007; Dignum and Tick 2008). Agent-based models (ABMs) are computational constructs used to simulate the actions and interactions of autonomous agents in order to evaluate their impacts on the system as a whole (Axelrod 1997). Indeed, it has been demonstrated that ABMs are predictive and analytical research tools that can provide insights into complex social behaviour and generate new theory (Johnson 2011). Chappin et al. (2007) pointed out that, while ABMs originate from research domains such as artificial intelligence and social science, they are flexible enough to be used in a wide range of applications. Clarke (2014) indicated that ABMs are preferred when the goal of the model is the simulation of a behavioural unit, such as a person or household, and when the model represents interactions among one or more types of agent. The versatility of agent-based modelling and simulation (ABMS) has demonstrated in a variety of domains such as: disaster response (Kwan and Lee 2005; Mysore et al. 2006; Saoud et al. 2006); emergency evacuation (Ren et al. 2009; Wagner and Agrawal 2014); investigating business relationships and networks (Blackmore and Nesbitt 2009; Huang and Wilkinson 2013); risk-based flood incident management (Dawson et al. 2011). While ABMS is proposed as a suitable approach to investigate SMEs' response and recovery from a flood, it is

recognized that other approaches exist such as simulation-based serious gaming which can be used to understand business concepts, explore different situations and support decision making in operations management (De Gloria et al. 2014; Van Der Zee et al. 2012).

This paper presents progress made in the initial stages of the development of an ABMS framework to enable assessments of the effects of a range of SMEs' preparatory and responsive behaviours in relation to their recovery from flooding.

### 2. OVERVIEW OF ABMS FRAMEWORK

The research carried out to date and reported in this paper builds on earlier work (Coates et al. 2014; Li and Coates 2016). The aim of this research is to develop and use ABMS to assess the recovery of flood-affected SMEs' from a variety of industrial sectors. Further, a more comprehensive range of preparatory and responsive SME behaviours will be modelled than seen previously, including those related to promoting greater co-operation between SMEs. Such co-operative behaviours can contribute to flood-affected businesses maintaining some level of operations during (via mutual aid) and in the immediate aftermath of a flood event. To achieve this aim, the research has been divided into two main parts:

- 1. Enabling the identification of SMEs affected by a simulated flood event in a specified geographical area.
- 2. Modelling SMEs as agents (and other related organisations), with behaviours and attributes, identified in the specified geographical area to enable the simulation of these businesses in the post-flood recovery stage.

As indicated in Figure 1, within the ABMS framework being developed, a geographical environment is modelled that takes dynamic inundation data as its input from the simulation of a flood event. The modelled geographical environment (MGE) uses Ordnance Survey (OS) data, combined with the inundation data, to enable the identification of each individual business flooded over the timeline of the flood event simulated. Subsequently, flooded-affected businesses, in addition to those unaffected by flooding and other related organisations, are to be modelled as autonomous agents and simulated before, during and after a flood event.



Figure 1: ABMS Framework Overview

SMEs from various industrial sectors, including manufacturing, will be modelled according to behaviours specific to that sector of business. These behaviours of SMEs from a range of industrial sectors

have been identified from semi-structured interviews with businesses that have experience of flooding, along with academic and government agency advisory literature. Currently, at this early stage of the research, only manufacturing SMEs have been modelled as agents, with each exhibiting only several pre-flood and post-flood SME behaviours.

## 3. FLOOD SIMULATION AND GEOGRAPHICAL ENVIRONMENT MODELLING

Prior to the research reported in this paper, the severe flood event of 2007 in Sheffield's Lower Don Valley in the UK was simulated. This geographical area was selected due of its high concentration of SMEs from a range of industrial sectors, some of which have experience of flooding and/or are prone to flooding. Flood event simulation generated a series of inundation data files, each of which represented the water depth throughout the area modelled at 30 minute intervals over a 45.5 hour period, i.e. the duration of the actual 2007 flood event. The flood footprint based on a single inundation data file, corresponding to 25 hours after the flood event commenced, is shown in Figure 2(a).

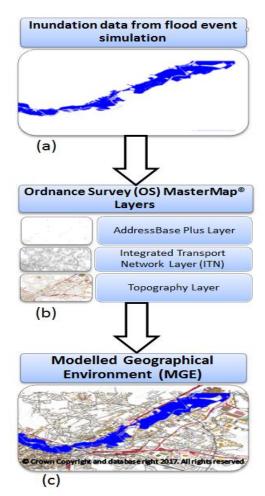


Figure 2: Process of Identifying Flooded SMEs

The inundation data forms the input to the MGE, which is made up from three layers of OS MasterMap®

(Ordnance Survey, 2017) as indicated in Figure 2(b). Specifically, the Topography layer provides data on individual buildings and the Integrated Transport Network (ITN) layer contains data on the road network. In addition, the AddressBase Plus layer provides data related to commercial properties including business name, precise location and classification, as well as other attributes such as number of floors in the premises. Superimposing the inundation data with the MGE's three layers of OS MasterMap® forms a visual representation of Sheffield's Lower Don Valley as shown in Figure 2(c). As stated earlier, inundation data, i.e. the depth of flood water at locations in the geographical area modelled, varies dynamically. Figure 3 shows inundation data, coupled with the OS layer data, at a series of time intervals. That is, at the time the flood commenced (t=0 hours), then 5, 14, and 23 hours after the flood commenced. In Figure 3, two SMEs are highlighted, 'A' and 'B', as these will be referred to in Section 4 in the context of preliminary simulations.

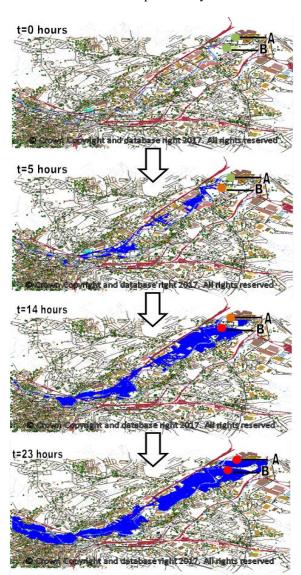


Figure 3: Flood Footprints Based on Inundation Data

In Figure 3, the colour used to represent SMEs 'A' and 'B' signifies the status of the premises of the respective business at the specified time: green for not-flooded; amber for flooding commenced; red for flooded. Throughout the geographical area modelled, the flooded and non-flooded SMEs can be seen as illustrated in Figure 4.



Figure 4: Identified Flooded and Non-flooded SMEs

Based on the MGE and inundation data, in Sheffield's Lower Don Valley, 6224 organizations were identified with 906 flooded at some point during the 45.5 hour event modelled. Table 1 presents a breakdown of these organizations according to the International Standard Industrial Classification of all Economic Activities (ISIC) (United Nations 2008).

Table 1: Organizations in Sheffield's Lower Don Valley

ISIC	Organizations	
	Flooded	Not flooded
Administrative services	116	802
Accommodation services	41	406
Agriculture/forestry/fishing	2	1
Arts and entertainment	13	75
Education	2	76
Electricity/gas/steam	0	7
Finance	3	68
Households as employers	1	36
Human health / social work	1	127
Information/communication	2	17
Manufacturing	256	1207
Mining and quarrying	0	10
Other service activities	4	25
Professional services	47	234
Public administration	7	78
Real estate activities	56	769
Retail	13	253
Transportation and storage	337	1071
Water	5	56
Total	906	5318

For the purposes of this research, businesses were mapped from the OS business classifications to the ISIC given this is a more recognizable sector categorization. In relation to Table 1, it is noted that the Environment Agency (2007) indicated that more than 1000 businesses were impacted by the 2007 flood event. The disparity between the EA's indication and the 906 businesses identified in this research may be accounted for by the ten year difference between the actual flood event in 2007 and the OS's AddressBase Plus layer dataset from 2017.

As stated in Section 2, at this stage of the research, only manufacturing SMEs have been modelled as agents; albeit at a fundamental level so far. The manufacturing sector was chosen due to SMEs in this sector suffering significant economic losses and damage to their premises, equipment and machinery due to the flooding in 2007 (Environment Agency 2007). Also, according to the OS AddressBase Plus layer dataset used in this research, the manufacturing sector accounted for the largest number of businesses within the geographical area modelled (as presented in Table 1) including both flooded and non-flooded businesses (n=1463).

## 4. PRELIMINARY AGENT-BASED SIMULATIONS OF MANUFACTURING SMFS

In this research, the Recursive Porous Agent Simulation Toolkit (Repast) is being used to carry out ABMS (Collier and North 2011). Repast has been reported as an appropriate framework for applied modelling of social interventions based on current theories and data (Tobias and Hofmann 2004, Balbi and Giupponi 2009). Also, Repast is viewed as amongst the most effective simulation toolkits in terms of its capability of modelling complex systems (Arunachalam et al. 2008). Robertson (2005), along with Railsback et al. (2006), have indicated that one of Repast's strengths is that it was created and developed by social scientists, which facilitates that it supports projects which entail social networks, generic algorithms, systems dynamics and geographical information systems (GIS).

### 4.1. Agent Modelling of Manufacturing SMEs

Initial simulation work has focused on modelling manufacturing SMEs as agents based on their size (i.e. micro, small or medium) which, as referred to in Section 1, is associated with number of employees. According to statistical data related to businesses in the UK, 99.9% of all businesses are SMEs with 96%, 3.3% and 0.6% being categorized as micro-, small- and medium-sized respectively (White 2016). Thus, the 1463 manufacturing SMEs (see Table 1) have been modelled in these proportions, then randomly allocated a number of employees corresponding to their respective size, as indicated in Figure 5. For example, 246 of the 256 flood-affected manufacturing SMEs, i.e. 96%, are modelled as micro-businesses, which have between 1 and 9 employees (inclusive).

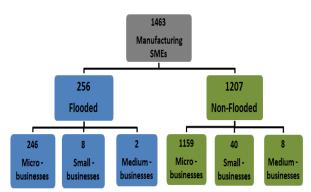


Figure 5: Allocation of Manufacturing SMEs

Flooded manufacturing SMEs are modelled as agents with static attributes including business name, classification code, classification name, size, number of employees, and coordinates of its premises location. Also, from inundation data generated by the flood event simulation, for each manufacturing SME the depth of flood water at 30 minute intervals over the 45.5 hour event period is known. As indicated in Figure 6, the duration of a typical simulation is 21 days which has been divided into three stages: pre-flood; during flood; post-flood. In each day simulated, the 24 hour period is represented by 48 simulation ticks, i.e. one tick per 30 minute period. Furthermore, in each day simulated, working hours start at clock time  $t_c$ =8:00 and finish at  $t_c$ =18:00, which corresponds to 20 simulation ticks.

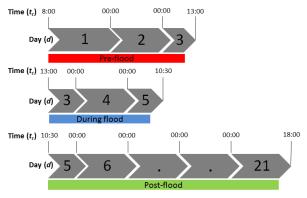


Figure 6: A Typical Simulation Duration (clock hours)

In a typical simulation duration as indicated in Figure 6, the pre-flood stage starts at  $t_c$ =8:00 on day 1 until the flood event occurs at  $t_c$ =13:00 on day 3. However, the time at which the flood water reaches a particular SME's premises will vary slightly depending on the actual geographical location of the property in the flood affected area. The 'during' flood stage begins at  $t_c$ =13:00 on day 3 until the flood water recedes at  $t_c$ =10:30 on day 5 given the event modelled has a duration of 45.5 hours. Again, the time at which the flood water recedes from an SME's premises will vary on its location. Post-flood begins from the time the water recedes from an SME's premises until  $t_c$ =18:00 on day 21. The period of disruption for an SME begins at the point at which the flood water enters its premises, or at the point the business begins preparing for the

flood event (pre-flood), thus reducing or halting production, and ends when it has returned to normal production (post-flood). The term 'normal production' refers to when an SME has resumed its pre-flood level of production. During this period of disruption, manufacturing SMEs' production levels will fall. Business that are flooded will experience their production level fall to zero for a period of time, then gradually recover based on preparatory and response behaviours. In contrast, SMEs threatened by flooding rather than actually being flooded, will see a reduction in production level while preparatory behaviours are enacted, then a resumption of production depending on the degree to which the flood event has disrupted distribution, supply, and other external factors.

In addition to static attributes such as those mentioned earlier, SME agents have dynamic attributes including raw materials (RM), machines (M), employees (E) and power (P). The relationships between these dynamic attributes are represented in Figure 7, demonstrating that the availability of each is necessary for production.

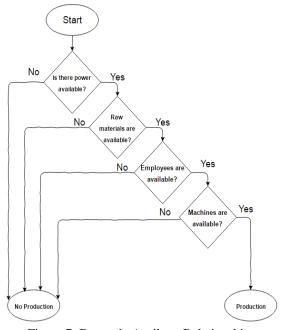


Figure 7: Dynamic Attribute Relationships

These attributes change during the course of the simulation and contribute directly to the SMEs' performance, which is measured as production level (PL) in this research. Given the flood event is simulated at 30 minute intervals, each of which corresponds to 1 simulation time step or tick  $(t_s)$ , then the production level is determined at each half hour interval (or tick) throughout the 21 day period simulated. Post-flood, a flood-affected manufacturing SME's production level can be resumed if:

(a) the power supply is restored to the premises, i.e. P = 1 (P = 0 indicates that an SME's premises has no power and thus cannot resume the manufacture of products);

- (b) raw materials are available, RM > 0, where RM is the sum of raw material units stored on the ground,  $RM_{og}$ , and above ground,  $RM_{ag}$ ;
- (c) machines are available, M > 0, where M is the ratio of an SME's available machines,  $M_a$ , to the total number of machines  $M_t$ ;
- (d) production employees are available,  $E_a^p > 0$ , and E > 0 which is the ratio of the number of available production employees working on production,  $E_p^p$ , to the total number of production employees,  $E_t^p$ .

In relation to (d),

$$E_t^p = 0.81 \times E_t \tag{1}$$

where the total number of employees,  $E_t$ , is the sum of the total number of production employees,  $E_t^p$ , and the total number of non-production employees,  $E_t^{np}$ . Correspondingly,

$$E_t^{np} = 0.19 \times E_t \tag{2}$$

The value 0.81 has been used in equation (1) since, according to the Department of Business Innovation and Skills (BIS 2010), within a *typical* manufacturing business 48.7% of employees work directly in production and 32.1% work in production-related roles. The remaining 19.2% of employees work in roles that are not related to production, such as sales and marketing. Thus, each of the manufacturing SME agents has been assigned 81% of the total employees as being related to production and 19% as being related to non-production.

In terms of the consumption of raw materials during production, if P = 1,  $RM \ge 1$ , M = 1 and E = 1, then in each 30 minute period a single unit of RM is used and, consequently, production level PL = 100%. That is, in that half hour period, the premises has power, the raw materials available exceeds or is equal to the unit to be used, all machines are available  $(M_a = M_t)$ , and all production employees are available and work on production  $(E_p^p = E_a^p = E_t^p)$ . However, still with power to the premises and sufficient raw materials available, if not all machines and/or production employees are available, i.e. M < 1 and/or E < 1, then only a fraction of a unit of raw materials will be used for production (with PL < 100%) during the associated 30 minute period. Note that, while in all SMEs a maximum of a single unit of raw materials can be consumed in a 30 minute period (as described above), the size of a unit of raw material varies according to the total number of production employees in that SME. For example, for an SME with  $E_t^p = n$ , each employee will use 1/n units of raw material in a 30 minute period. The code to determine the production level in a 30 minute period, i.e. a simulation tick, is presented in Algorithm 1.

# 1. **if** P = 1 **then**2. { 3. **if** raw materials at time t, $RM_t \ge 1$ **then**4.

 $PL = \min \{E, M\} \times 100$ 

 $RM_{t+1} = RM_t - \min\left\{E, M\right\}$ 

**Algorithm 1:** Determining Production Level (*PL*)

17.  $PL = RM_t \times 100$ 18.  $RM_{t+1} = 0$ 19. }
20. }
21. **else if**  $RM_t = 0$ 

22. {
23. PL = 024.  $RM_{t+1} = 0$ 26. }

5.

6.

27. **else if** P = 028. { 29. PL = 030.  $RM_{t+1} = RM_t$ 

31.

In Algorithm 1, for each simulation tick, (a) production level and (b) raw materials available at the next tick, are determined depending on whether power is available at the SME's premises (lines 1 to 26) or not (lines 27 to 31). For situations in which power is available, and depending on the amount of raw materials available at the current tick, both (a) and (b) are determined according to the relationship between ratios of production employees working on production to total number of employees, and machines available to total number of machines respectively. Although not included in the algorithm, an SME re-orders raw materials at regular intervals except from the time flooding commences until the flood water recedes from its premises. For example, in relation to Figure 8, at the beginning of the pre-flood period simulated ( $t_s$ =0), the SME is modelled as having 100 units of raw materials available (point (a)), which corresponds to the maximum amount required to operate at 'normal' production (i.e. PL = 100%) for one working week providing all production employees work production. The SME consumes raw materials each working day (i.e. 10 clock hours or 20 simulation ticks) until production is stopped due to flooding (at  $t_s$ =144).

During the flood ( $t_s$ =144 to  $t_s$ =197), raw materials may be damaged depending on how much is stored at ground level and above ground level, and the flood water depth in the SME's premises. During the first day after the flood water has receded from the SME's premises, raw materials are re-ordered, which are delivered at the start of the following day as indicated by point (b) in Figure 8. Subsequently, the SME consumes raw materials and re-orders at 5 day intervals. In Figure 8, post-flood, it is noted that raw materials do not always reduce to zero at the end of each working week (points (c) and (d)) due to only a proportion of production employees returning to work, thus working on production, and/or only a percentage of machines being available.

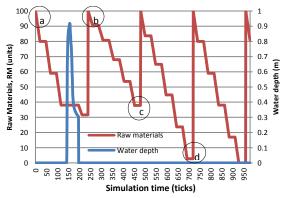


Figure 8: Demonstration of Re-ordering Raw Materials

### 4.2. Preliminary Agent-based Simulations

As mentioned in Section 4.1, for each SME, the PL is determined at each 30 minute interval throughout the three periods (pre, during, post) of the flood event modelled. Pre-flood, which can last up to between 21/2 or 3 days ( $t_s$ =0 to  $t_s$ =120 or  $t_s$ =144 ticks in a simulation), PL is 100% before any disruption to an SME's operations. However, PL drops to zero if the flood water enters an SME's premises and remains at this level during the flood. Post-flood, at some point, production resumes and thus PL starts to recover depending on the depth the flood water reached in the premises during the flood and its impact on P, RM, M and E. That is, the time at which production is resumed and rate at which it resumes is dependent on the level of damage to machines and raw materials caused by flooding, the distribution of production employees returning to work in the immediate aftermath of the event, and whether or not the premises has power given that it may have been lost during the flood event. At the start of all simulations, each SME has 100 units of raw materials with one unit being consumed per simulation tick providing all production employees are working on production. Given there are 20 simulation ticks per working day (i.e. from  $t_c$ =8:00 to  $t_c$ =18:00), then, again providing all production employees are working on production, an SME will consume 20 units of raw materials per working day or 100 units per working week. Initially, an SME stores 75 units of raw materials on the ground,  $RM_{og}$ , and 25 units above ground at a height of 2.5 metres (m),  $RM_{aa}$ , where the above

ground storage capacity is 50 units ( $RM_{ag}^c = 50$ ). During simulations, on the delivery of raw materials to an SME's premises which occurs every 5 working days, 25 units are stored above ground if storage capacity allows, and 75 units at ground level.

In the following sub-sections, two micro-sized manufacturing SMEs, referred to as 'A' and 'B', which experience different severities of flooding, are considered in terms of how production level was affected by the flood event simulated given these businesses enacted pre- and/or post-flood behaviours:

- (a) Pre-flood: on receiving a flood alert from the EA agent, each production employee either lifts-up raw materials from ground level to store them above ground level (see equation (3)) or works on production (see equation (4));
- (b) Post-flood: after the flood water has receded from the premises, repair machines at a rate 0.5% of machines per simulation tick either:
  - (i) by employing a single production employee, if available, while all others work on production, or;
  - (ii) dividing available production employees such that a number work on repairing machines (equations (5)) while the remainder work on production (equation (7)).

In relation to behaviour (a), the EA issues flood alerts approximately 3 hours before the flood commences, which, if production employees are available, leads to raw materials being lifted-up from the ground to above ground level. Note that (b) is enacted during working hours (i.e. from  $t_c$ =8:00 to  $t_c$ =18:00) providing the EA alert is received during this time or less than 3 hours from the start of the working day (i.e. after  $t_c$ =5:30). Outside these hours, no employees are available to save raw material stored at ground level should the water enter the premises. For behaviour (a), production employees are divided such that they either lift-up raw materials, thus avoiding damage, or continue with production. The number of production employees allocated to lifting-up raw materials,  $E_l^p$ , at any simulation tick,  $t_s$ , as

$$E_l^p = min\left(E_a^p, \left\lceil \frac{RM_{ag}^c - RM_{ag}}{n_{rm}} \right\rceil, \left\lceil \frac{RM_{og}}{n_{rm}} \right\rceil \right) \tag{3}$$

where  $n_{rm}$  units of raw materials can be lifted-up per production employee per simulation tick (in this paper,  $n_{rm} = 6$ ). Thus, the number of available production employees working on production,  $E_p^p$ , is defined as

$$E_p^p = E_q^p - E_l^p \tag{4}$$

In relation to behaviour (b)(ii), in a simulation, the percentage of machines damaged is based on the depth that the flood water reaches in an SME's premises. Production employees available,  $E_a^p$ , will work on both

repairing machines, should any need repairing (i.e.  $M_a < 100$ ) and production. This division of available production employees can be defined according to different strategies. In this paper, the strategy employed determines the number of production employees selected to work on repairing machines,  $E_r^p$ , at any simulation tick,  $t_s$ , as

$$E_r^p = max \left( 1, E_a^p - \left( \left[ M \times E_t^p \right] \right) \right) \quad \text{if} \quad E > M \quad (5)$$

$$E_r^p = 0 if E \le M (6)$$

Thus, the number of available production employees working on production,  $E_n^p$ , is defined as

$$E_n^p = E_a^p - E_r^p \tag{7}$$

This strategy ensures that all production employees are assigned to production if there are sufficient machines available for them all to work on. However, if more production employees are available than there are machines available, then the surplus of these employees is assigned to repair damaged machines.

### 4.2.1. Manufacturing SME 'A'

For SME 'A', the flood commenced at  $t_s$ =137 ( $t_c$ =4:00 with  $RM_{og}$  = 55,  $RM_{ag}$  = 25,  $M_a$  =100%) and receded at  $t_s$ =174 ( $t_c$ =22:30 with  $RM_{og}$  = 0,  $RM_{ag}$  = 25, and  $M_a$  = 40%) reaching a depth of 1.1m in the premises, as indicated in Figure 9. The flood duration of 37 ticks (i.e. 18.5 hours), coupled with the depth of water reached, led to 60% of machines being damaged. Furthermore, this SME had a total of six production employees ( $E_t^p$  = 6) but only five available ( $E_a^p$  = 5) in the first and second day after the flood water receded, then all six available thereafter.

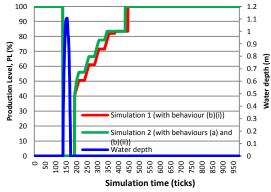


Figure 9: SME 'A' - Production Level and Flood Water Depth in Premises

In Figure 9, two simulations are shown. The red line represents simulation 1 in which SME 'A' has behaviour (b)(i) and the green line signifies simulation 2 in which it has behaviours (a) and (b)(ii). Given the flood commenced outside working hours, ( $t_c$ =4:00), the SME 'A' was unable to respond to the flood alert

received from the EA agent at  $t_s$ =131 ( $t_c$ =1:00) in simulation 2. Thus, in both simulations 1 and 2, the SME did not lift-up any raw materials stored at ground level leading to all 75 units being destroyed. However, the 25 units stored above ground level at 2.5m were unaffected by the flood water which reached 1.1m. Once the flood water had receded, employees returned to work at the start of the next working day,  $t_s$ =193. At this time, in both simulations, production resumed immediately reaching a level of 40% as governed by the ratio of machines available (0.4), i.e. 40% of machines were available for production.

Subsequently, in simulation 1, a single production employee repaired machines at a rate of 0.5% per tick such that in each working day (20 ticks) 10% of those damaged were repaired and made available for production. At the same time, all remaining employees worked on production from  $t_s$ =193 to 386, during which time production level increased steadily from 40% to 83%. During the first day of this period of production, raw materials stored above ground were consumed since those stored on the ground were destroyed during the flood. A delivery of raw materials at the start of the second day after the flood replenished those stored on the ground to 75 units and above ground to 25 units. Subsequently, from  $t_s$ =387 to 447, production level remained constant at 83% since during this period the number of production employees was less than the machines available. Furthermore, during this period, 27.6 units of raw materials were consumed. At  $t_s$ =447 (i.e. 6 days after the flood), when all machines had been repaired and all production employees were able to work on production, *PL*=100%.

In contrast, for simulation 2, after reaching 40% at  $t_s$ =193 (with  $RM_{og} = 0$ ,  $RM_{ag} = 25$ , and  $M_a = 40\%$ ), production level increases at a faster rate than in simulation 1 due to two of the five available production employees repairing machines  $(E_r^p = 2)$  while three worked on production  $(E_p^p = 3)$  in accordance with equation (5). After 5 hours in the first working day postflood, at  $t_s=204$  (with  $RM_{og}=0$ ,  $RM_{ag}=19.4$  and  $M_a = 51.5\%$ ), one of the two production employees allocated to repairing machines was reallocated to production. From this time until a point during the fourth day post-flood (t<sub>s</sub>=347), production level increased to 83% with only one production employee repairing machines while the other five worked on production. From  $t_s$ =348 to 435, during which time a delivery of raw materials occurred, the production level was governed by the number of employees available, remaining at 83% since  $E_p^p = 5$  and  $E_a^p = 6$ , rather than the number of machines available. At  $t_s$ =435, the available machines reached 100%, and thus all production employees worked on production leading to PL=100%. It is observed that the behaviours associated with each of simulation 1 and 2 led to a difference in the time to resume a production level of 100% of 6 hours (447-435=12 ticks).

### 4.2.2. Manufacturing SME 'B'

As shown in Figure 10, SME 'B' operates at 100% production pre-flood until flood water enters its premises at  $t_s$ =119 ( $t_c$ =19:00). During the flood, from  $t_s$ =119 to  $t_s$ =198, the water in the premises reached a depth of 2.2m. This depth of water reached, along with the SME's premises being flooded for 79 ticks (i.e. 39.5 hours), caused all machines to be damaged ( $M_a = 0\%$ ) and thus be in need of repair. SME 'B' has a total of five production employees ( $E_t^p = 5$ ) of which only four return to work in the first day after the flood water receded ( $E_a^p = 4$ ); in the following day the fifth production employee returned to work. In Figure 10, two simulations are shown, as referred to in relation to Figure 9 in Section 4.2.1, with the red and green lines representing simulation 1 and 2 respectively.

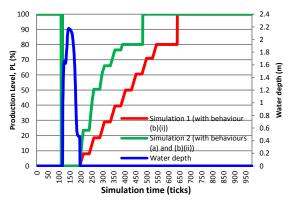


Figure 10: SME 'B' - Production Level and Flood Water Depth in Premises

In simulation 1, from  $t_s$ =198 to 640, with raw materials stored above ground being immediately available, along with subsequent deliveries to the SME's premises, production level increases in a gradual and almost linear fashion from 0 to 80%. During this period, production level was constrained by the ratio of the number of available production employees working on production to the total number of production employees (E=0.8 since  $E_p^p = 4$  and  $E_t^p = 5$ ;  $E_r^p = 1$ ) as this is less than the ratio of an SME's available machine to the total number of machines (0.8 <  $M \le 1$ ). Later, at  $t_s$ =641, when all machines were repaired and all production employees available to work on production, *PL*=100%. In relation to simulation 2, at  $t_s$ =113 ( $t_c$ =16:00) a flood alert was received from the EA agent and thus all the available production employees were allocated to lift-up raw materials from the ground to above ground level in accordance with equation (3) where  $E_a^p = 5$ ,  $RM_{ag} = 25$  and  $RM_{og} = 32$ . As a result of this, at  $t_s=113$ , the raw materials lifted-up to above ground level reached capacity, i.e.  $RM_{ag} = 50$ . Subsequently, production was resumed until the end of the working day; the flood water entered the premises afterwards at  $t_s=119$ ( $t_c$ =19:00). On the first working day after the flood, at  $t_s$ =198 (with  $RM_{og} = 0$ ,  $RM_{ag} = 50$ , and  $M_a = 0\%$ ), all available production employees ( $E_a^p = 4$ ) were allocated to repair machines. Thus, by the end of tick  $t_s$ =198, 2% of the machines were repaired enabling one production employee to be allocated to production at the following tick. Next, at  $t_s$ =212, with sufficient raw materials available and  $M_a = 21.5\%$ , one of the production employees repairing machines reallocated to work on production. Following this, from  $t_s$ =212 to 240, two production employees worked on repairing machines while two worked on production. At  $t_s$ =241, which is the beginning of the second day after the flood, the fifth production employee returned to work and was allocated to repairing machines leading to PL=23.5%. At  $t_s=253$ , with  $M_a=41.5\%$  due to machines being repaired, one of the production employees repairing machines was reallocated to production leading to PL=41.5%. With this allocation of production employees, from  $t_s$ =253 to 391, production increased from 41.5% to 80%. From  $t_s$ =391 to 483, production level was governed by the ratio of production employees working on production (*E*=0.8). At  $t_s$ =484, with all machines repaired and thus all production employees working on production, PL=100%. Comparing both simulations, it can be seen that in simulation 2, SME 'B' returned to 100% production 78.5 hours (641-484=157 ticks) earlier than in simulation 1 which can be attributed to applying behaviours (a) and (b)(ii) rather than (b)(i).

### 5. CONCLUSION AND FUTURE WORK

This paper has provided an overview of the initial development of an ABMS framework to assess SMEs' recovery from flooding. For a particular case study area, namely the Lower Don Valley region of Sheffield in the UK, in which the severe 2007 flood event has been simulated, flood-affected businesses have been (a) identified using a modelled geographical environment then (b) represented as agents in preliminary simulations. More specifically, manufacturing SMEs were selected to be modelled as agents given this type of business experienced severe damage to their premises and disruption to their operations as a result of the 2007 flood event. Preliminary simulations carried out showed that a micro-sized SME's recovery from flooding, in terms of production level, depends not only on the depth of water reached in their premises and the number of production employees available, but also on the behaviours of the business pre- and post-flood.

Future research will involve developing comprehensive set of pre- and post-flood behaviours for SMEs from the manufacturing and other industrial sectors based on data gathered from semi-structured interviews with small businesses having experienced flooding. For example, pre-flood behaviours will include erecting physical flood defences and raising electrical points. Post-flooding behaviours will include cooperating with other businesses unaffected by flooding to facilitate 'mutual-aid' operation across different locations. In addition to modelling SMEs, agents will be developed to model organisations such as customers, suppliers and service companies. Also, simulation experiments will be defined and performed

to evaluate the effect of different behaviour combinations on SMEs' recovery from flooding. Finally, once the agent-based model has been fully developed and SME behaviours investigated via simulations, outcomes will be discussed with SMEs.

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