Modelling Crowd Dynamics in Bio-PEPA –Extended Abstract–

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Emergent phenomena occur due to the pattern of non-linear and distributed local interactions between the elements of a system over time. An example of such phenomena is the spontaneous self-organisation of drinking parties in the squares of cities in Spain, also known as "El Botellón" [16]. Surprisingly, crowd models in which the movement of each individual follows a very limited set of simple rules often re-produce quite closely the emergent behaviour of crowds that can be observed in reality. In this paper we take a stochastic process algebraic approach to agent based modelling. In this setting, a single stochastic process algebraic model can be used for several forms of analyses among which simulation, stochastic model-checking and fluid flow analysis. Here we revisit the case of self-organisation of crowds in a city. We show that a fluid flow approximation, i.e. a deterministic reading of the average behaviour of the system, can provide an alternative and efficient way to study the same emergent behaviour as that explored in [16] where simulation was used instead. Scalability features of this approach may make it particularly useful when studying models of more complex city topologies with very large populations.

1 Introduction

In modern society the formation of crowds, intended as large concentrations of people, is a phenomenon that occurs frequently. Well known examples are crowds at large entertainment events in cities or other open-air facilities such as sport stadiums, but also crowds at large airports and train stations. Fortunately, such crowds usually occur and dissolve without serious problems. However, in some cases serious accidents happen with possibly major consequences such as loss of lives and a large number of injuries [18]. The recent drama at the open-air festival in Germany is sadly adding to the list of such events [1].

There is an ever stronger interest in being able to prevent such disasters and there exists an extensive literature on numerous approaches to the study of crowd formation, crowd management and emergency egress [17]. Simulation models play an important role in these approaches. In particular, agent based modelling has become popular in recent years because it may provide valuable information about the dynamics of systems that contain non-linear elements, chaos and random cause and effect. Several works in this area, e.g. work by Still [18], show that a crowd of people in which each individual follows a very limited number of simple rules produces quite closely the emergent behaviour that can be observed in real human crowds. Emergent phenomena are known to occur due to the pattern of non-linear and distributed local interactions between the large number of elements of a system over time. In particular, work by Still shows that such simple local rules are in many cases sufficient to produce the observed behaviour and that no complicated rules of group behaviour or psychological parameters are necessary. His work and that of others have led to the development of several professional tools, based on agent simulation, for the realistic analysis and prediction of crowd behaviour in emergency situations. Such analyses may

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help to detect architectural or organisational problems that may potentially cause loss of lives in the event of emergency situations occurring in, for example, airports, sport stadiums and open-air festivals.

However, for very large crowds, analysis via simulation may become time-consuming since each execution of the model produces only a singe trajectory through the state space whereas many executions are needed to reach statistically relevant conclusions. Therefore, the costs of simulation based analysis often becomes prohibitive in situations in which a quick analysis is required to compare the consequences of different design options or when a large number of slightly different scenarios need to be analysed.

Recently, a process algebraic approach has been proposed that provides a high level formalism to express the autonomous behaviour of individual agents and their interaction. The formalism is supported by several analysis methods among which is a scalable fluid flow approximation of the behaviour of the system that gives rise to a set of ordinary differential equations (ODEs) [12]. To illustrate the use of this approach, we revisit the case of self-organisation of crowds in a city as described by Rowe and Gomez in [16]. We show that a fluid flow approximation can provide an alternative and efficient way to study the same emergent behaviour as that explored in [16] where simulation was used instead. In that work the movement of a crowd in a city is studied under various assumptions about the likelihood that people remain in a square. The work was inspired by a typical phenomenon observed in Spanish cities, on summer nights, called "El Botellón", when crowds of youngsters wander between city squares in search of a party. Such self-organised parties sometimes lead to heavy drinking and noisy behaviour until late at night. Moreover, it turned out to be hard to predict when and where a large party would take place. The aim of the work by Rowe and Gomez was to gain insight into the conditions under which parties self-organise. In their study agents follow two basic rules. The first rule defines when agents remain in a square, which depends on the "chat-probability", i.e. the likelihood to meet someone in the square to chat with. The second rule defines how agents move between squares. If an agent finds nobody to chat with it goes randomly to any neighbouring square.

Rowe and Gomez develop a mathematical model to approximate the threshold of this chat-probability below which people are freely moving through the city and above which large crowds start gathering in just a few squares. They validated their theory by the simulation of a multi-agent model for a regular city topology of 4 squares and up to 80 agents. Both the theory and the simulation results show that for a value of the chat probability $c = n/N$, where n is the number of squares and N the number of agents, a clear phase-transition can be observed between a steady-state situation in which agents are evenly distributed over the squares (when c is below the threshold) and a situation in which agents spontaneously gather in one or a few squares (when c is a above the threshold).

We approach the modelling of crowds moving between city squares by adopting the Bio-PEPA stochastic process algebra [9] which is enhanced with both an efficient analysis technique, i.e. *fluid flow approximation*, and with stochastic simulation techniques. Bio-PEPA was originally devised for modelling bio-molecular interaction. It embeds a notion of spatial location, intended to model biological compartments, which allows us to describe the city topology and locate agents within it. Moreover, the agent behaviour can be expressed as a function of the current state of the system, like the number of people present in a square, an abstraction of the act of sensing the environment, common to standard agent models. Such a function may contain non-linear elements, which makes Bio-PEPA also particularly interesting for the analysis of some forms of emergent behaviour, as we will see in later sections. In previous work on the use of fluid flow approximations in the context of emergency evacuation from buildings we have considered linear differential equations [14, 4]

By adopting this approach, we gain an expressive linguistic description of agent behaviour from process algebras, which can be thought of modularly, can be easily revised, is grounded on a neat formal semantics also encompassing the stochastic aspects, and is supported by a suite of computational tools.

Fluid flow approximation aims at tackling the state space combinatorial explosion that arises as a consequence of interleaving the behaviour of the many independent individuals. Fluid flow relies on an abstract quantitative description of the system, i.e. variables represent amounts of agents with independent but "homogeneous" behaviour, and on the approximating hypothesis that such quantities vary continuously over time. Intuitively speaking, the continuity hypothesis can be understood as an acceptable approximation in the presence of large numbers of agents, as for the cases of our interest, and considering that these quantities vary over time by small discrete steps, one or few units, negligible with respect to the large numbers involved. The high level process algebraic model can be automatically turned into a system of ODEs, which efficiently approximate the averaged behaviour of the system. We show that the fluid flow approach can also be used efficiently to explore and reproduce the results indicating the phase-transition observed in the study by Rowe and Gomez.

Furthermore, with this approach the agent view and the stochastic modelling are retained within a single framework, allowing the analysis of averaged and non-averaged behaviour to be carried out using the same model. For instance one may wish to understand and even tune the average behaviour of the system and then deepen some particular cases of interest. This may be particularly advantageous whenever the computational costs of stochastic simulation may only be justified when a final system design is considered, but would be prohibitive when exploring many design options and conditions during early phases of design. The analysis of the threshold for the self-organisation of crowds in a city is an example of such explorative analysis that would require many simulations to obtain an accurate view of the phase-transition. This is even more so when more complex city-topologies and a large number of agents are considered.

This extended abstract presents a limited selection of our results. For further results we refer to [15]. Section 2 recalls the crowd model used in the case study by Rowe and Gomez [16]. Section 3 briefly mentions Bio-PEPA and its analysis environment. Section 4 describes the Bio-PEPA model of the collective behaviour of crowds in a city followed by some analyses results in Sections 5. Finally, in Section 6 conclusions are presented and an outline of future research is given.

2 Rowe and Gomez Model of Crowd Dynamics

In this section we briefly recall the model of movement of crowds between squares in a city as presented by Rowe and Gomez in [16]. Assume a city with n squares represented as a graph with vertices $\{1,2,\ldots,n\}$. People are simulated by "agents" that are following a simple set of rules. The number of agents in square i, with $i \in \{0,1,\ldots,n\}$, at time t, with t representing discrete time steps, is represented by $p_i(t)$. The state of the system at t is given by the number of agents present in each square modelled by the vector $\mathbf{p}(t) = (p_1(t), p_2(t), \ldots, p_n(t))$. The total number of agents N at any time t is constant: $N = \sum_{i=1}^{n} p_i(t)$.

Agents are located in squares. The rules guiding agents' behaviour are the following. The probability that an agent decides to remain in a square depends on how many other agents are present in the same square. If a square i contains $p_i > 0$ agents, the probability that an agent *leaves* the square is given by $(1-c)^{p_i-1}$. The parameter c (representing the *chat probability*, $0 \leq c \leq 1$) is the probability that an agent finds another one to talk to and thus remains in the square. Consequently, if the population of square i is p_i then the probability for an agent to find nobody to talk to is $(1-c)^{p_i-1}$. Note that when there is only one agent in the square, it decides to leave with probability 1, since there is nobody else to talk to. If an agent decides to move, it moves with equal probability to any neighbouring square reachable by a street. Considering an analytical model of the above discrete behaviour the *expected* number of agents that will

leave square i at a given time step t is given by the function:

$$f_i(t) = p_i(t)(1-c)^{p_i(t)-1}$$

This models the part of the population in square i that does not find anyone to talk to in that square [1]. The probability that an agent, which decided to leave square j, moves to the adjacent square i is given by the matrix A_{ij}:

$$A_{ij} = \mathrm{con}_{ij}/d_j$$

where d_j is the degree of vertex j, i.e. the number of streets departing from square j, and con_{ij} denotes that square i is connected to square j:

$$\mathrm{con}_{ij} = \begin{cases} 1 & \text{if } i \text{ is connected to } j \\ 0 & \text{otherwise} \end{cases}$$

Clearly, $con_{ij} = con_{ji}$ and we assume that adjacent squares are connected by at most one street. The expected distribution of agents over squares at time $t+1$ can now be defined as:

$$\mathbf{p}(t+1) = \mathbf{p}(t) - \mathbf{f}(t) + A\mathbf{f}(t)$$

Clearly, from this formula it follows that a steady-state behaviour is reached when $\mathbf{f}(t) = A\mathbf{f}(t)$. In other words, when the number of people entering a square is equal to the number leaving the square. Rowe and Gomez show that there are two possibilities for such a stable state. In one case the agents freely move between squares and their distribution is proportional to the number of streets connected to each square. In the second case agents gather in large groups in a small number of squares corresponding to emergent self-organisation of parties. Which of the two situations will occur depends critically on the value of the chat probability c. In case all squares have the same number of neighbouring squares a phase shift occurs at about $c = n/N$ where n is the number of squares and N the number of agents. For $c < n/N$ people freely move between squares whereas for $c > n/N$ agents self-organise into large groups. Simulation of the model confirms in an empirical way that this estimate for c is quite accurate when the population is large enough where large means about 60 agents or more in a 4-square topology.

For topologies where each square has the same number of streets the critical value of c can be estimated in an analytical way. For less regular topologies and in case different squares have different chat probabilities and not all directions leaving from a square are equally likely to be taken by people it is very difficult to identify such critical values in an analytical way. Usually, in such cases simulation is used to analyse the models. However, when a large number of agents is involved, simulation may be extremely time consuming. In Section 4 we show that a combined process algebraic agent modelling and fluid flow approximation based on ODEs may provide a much faster way to obtain similar information for this class of models.

3 Bio-PEPA and Fluid Flow Analysis

In this section we give a short description of Bio-PEPA [8, 9, 7], a language that has recently been developed for the modelling and analysis of biochemical systems. The main components of a Bio-PEPA system are the *"species" components*, describing the behaviour of individual entities, and the *model*

[1] Note that in this analytical model the number of agents $p_i(t)$ in square i is now approximated by a real number: the *expected* number of agents in square i at time t.

component, describing the interactions between the various species. The initial amounts of each type of entity or species are given in the model component.

The syntax of the Bio-PEPA components is defined as:

$$S ::= (\alpha, \kappa)\ \mathtt{op}\ S \mid S + S \mid C \quad \text{with } \mathtt{op} = \downarrow \mid \uparrow \mid \oplus \mid \ominus \mid \odot \qquad P ::= P \underset{\mathscr{L}}{\bowtie} P \mid S(x)$$

where S is a *species component* and P is a *model component*. In the prefix term $(\alpha, \kappa)\ \mathtt{op}\ S$, κ is the *stoichiometry coefficient* of species S in action α. This arises from the original formulation of the process algebra for modelling biochemical reactions, where the stoichiometric coefficient captures how many molecules of a species are required for a reaction. However it may be interpreted more generally as the multiples of an entity involved in an occurring action. The default value of κ is 1 in which case we simply write α instead of (α, κ). The *prefix combinator* "op" represents the role of S in the action, or conversely the impact that the action has on the species. Specifically, $\downarrow$ indicates a *reactant* which will be consumed in the action, $\uparrow$ a *product* which is produced as a result of the action, $\oplus$ an *activator*, $\ominus$ an *inhibitor* and $\odot$ a generic *modifier*, all of which play a role in an action without being produced or consumed and have a defined meaning in the bio-chemical context. The operator "+" expresses the choice between possible actions, and the constant C is defined by an equation $C{=}S$. The process $P \underset{\mathscr{L}}{\bowtie} Q$ denotes synchronisation between components P and Q, the set $\mathscr{L}$ determines those actions on which the components P and Q are forced to synchronise, with $\bowtie$ denoting a synchronisation on all common actions. In the model component $S(x)$, the parameter $x \in \mathbb{R}^*$ represents the initial amount of the species.

A Bio-PEPA *system* with locations consists of a set of species components, also called sequential processes, a model component, and a context (locations, functional/kinetics rates, parameters, etc.). The prefix term $(\alpha, \kappa)\ \mathtt{op}\ S@l$ is used to specify that the action is performed by S in location l. The notation $\alpha[I \to J] \odot S$ is a shorthand for the pair of reactions $(\alpha, 1)\downarrow S@I$ and $(\alpha, 1)\uparrow S@J$ that synchronise on action α [2]. This shorthand is very convenient when modelling agents migrating from one location to another as we will see in the next section. Bio-PEPA is given an operational semantics [9] which is based on Continuous Time Markov Chains (CTMCs).

The Bio-PEPA language is supported by a suite of software tools which automatically process Bio-PEPA models and generate internal representations suitable for different types of analysis [9, 6, 3]. These tools include mappings from Bio-PEPA to differential equations (supporting a fluid flow approximation), stochastic simulation models [11], CTMCs with levels [8] and PRISM models [13].

A Bio-PEPA model describes a number of sequential components each of which represents a number of entities in a distinct state. The result of an action is to increase the number of some entities and decrease the number of others. Thus the total state of the system at any time can be represented as a vector with entries capturing the counts of each species component (i.e. an aggregated CTMC). This gives rise to a discrete state system which undergoes discrete events. The idea of fluid flow analysis is to approximate these discrete jumps by continuous flows between the states of the system. This approximation becomes good when entities are present in such high numbers as to make the frequency of actions high and the relative change from each single event small. In this case we can derive a set of ordinary differential equations (ODEs) which approximate the average behaviour of the CTMC.

4 Modelling Crowd Movement with Bio-PEPA

Let us consider the same small city topology with 4 squares, as in Rowe and Gomez and as shown in Fig. 1, allowing bi-directional movement between squares. The excerpt from the Bio-PEPA specification

[2] The concrete syntax for writing this currently in the Bio-PEPA tool set differs somewhat.

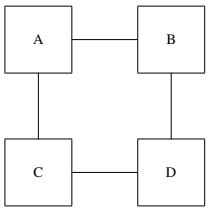


Figure 1: City plan with four squares

below defines this topology. The default compartment *top* contains all other compartments. The next line defines square *A*. Definitions for the other squares are similar and have been omitted. In this context *size* is used to denote a capacity in terms of number of agents.

$$\begin{array}{rcl} \mathit{location\ top} & : & \mathit{size} = 1000, \mathit{type} = \mathit{compartment}; \\ \mathit{location\ sqA\ in\ top} & : & \mathit{size} = \mathit{normal\_square}, \mathit{type} = \mathit{compartment}; \end{array}$$

The size of the squares, defined by parameter $\mathit{normal\_square} = 100$, is defined in such a way that all agents, 60 in this case, would fit in any single square and does not impose any further constraints. The Bio-PEPA specification, which we will henceforth refer to as the 'crowd model', has two further parameters. The parameter c defines the chat-probability and the parameter d the degree or number of streets connected to a square. In the topology presented in Fig. 1 $d = 2$ for all squares.

$$\begin{array}{rcl} \mathit{normal\_square} & = & 100; \\ c & = & 0.05; \\ d & = & 2; \end{array}$$

The actions modelling agents moving *f*rom square X *t*o square Y will be denoted by fXtY.

The associated functional rate (indicated by the keyword "kineticLawOf") is defined in analogy to [16] (see Section 2). Since the only information on the probability distribution available is the expected number of agents leaving a square per time unit, this same information can also be modelled as the rate parameter of an exponential distribution. In particular, letting $P@sqX$ represent the number of people currently in square X, such a rate is:

$$P@sqX * (1-c)^{(P@sqX-1)}$$

This models the rate of people leaving square X via any of its connecting streets leading to a neighbouring square. If one also considers the uniform distribution of people over the outgoing streets of the square then the above rate needs to be divided by its degree d when agents leaving through a particular street are considered. So the general rate with which agents leave square X via a particular street is:

$$(P@sqX * (1-c)^{(P@sqX-1)})/d$$

This leads to the following functional rates for the crowd model, one for each direction of movement. Only the one for fAtB is shown, the others being similar:

$$\mathit{kineticLawOf\ fAtB} \quad : \quad (P@sqA * (1-c)^{(P@sqA-1)})/d;$$

The sequential component P below specifies the possible movements of a typical agent between squares. For example, $fAtB[sqA \rightarrow sqB] \odot P$ means that an agent present in square A moves to square B according to the functional rate defined for the action $fAtB$.

$$\begin{aligned} P \quad = \quad & fAtB[sqA \rightarrow sqB] \odot P + fBtA[sqB \rightarrow sqA] \odot P + \\ & fAtC[sqA \rightarrow sqC] \odot P + fCtA[sqC \rightarrow sqA] \odot P + \\ & fBtD[sqB \rightarrow sqD] \odot P + fDtB[sqD \rightarrow sqB] \odot P + \\ & fCtD[sqC \rightarrow sqD] \odot P + fDtC[sqD \rightarrow sqC] \odot P; \end{aligned}$$

Finally, the model component defines the initial conditions of an experiment, i.e. in which squares the agents are located initially, and the relative synchronisation pattern. Initially, there are 60 agents in square A. This is expressed by $P@sqA[60]$ in the composition shown below. All other squares are initially empty (i.e. $P@sqX[0]$ for $X \in \{B,C,D\}$). The fact that moving agents need to synchronise follows from the defintion of the shorthand operator $\rightarrow$.

$$(P@sqA[60] \underset{*}{\bowtie} P@sqB[0]) \underset{*}{\bowtie} (P@sqC[0] \underset{*}{\bowtie} P@sqD[0])$$

The total number of agents $P@sqA + P@sqB + P@sqC + P@sqD$ is invariant and amounts to 60 in this specific case.

5 Some Results for a Model with Four Squares

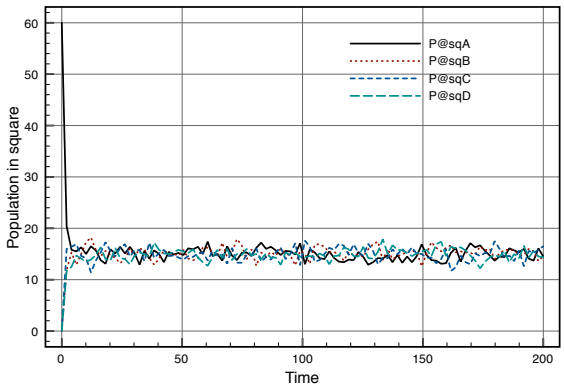
This section reports the analysis results for the model with four squares. The figures report both analysis via Gillespie stochastic simulation (G) [11], averaged over 10 independent runs, and fluid flow analysis based on the adaptive numeric solution of sets of ODEs based on the adaptive step-size 5th order Dormand-Prince ODE solver [10].[3]

Figure 2(a) reports stochastic simulation results for a model with 60 agents initially in square A and for a value of $c = 0.005$ which is below the analytical threshold of $c = n/N = 4/60 = 0.06666$. The results show that a dynamic equilibrium is reached, i.e. all agents distribute evenly over the four squares, which confirms the discrete event simulation results reported by Rowe and Gomez. Interestingly, the fluid flow analysis of the same model, Fig. 2(b), shows very good correspondence to the simulation results in Fig 2(a).

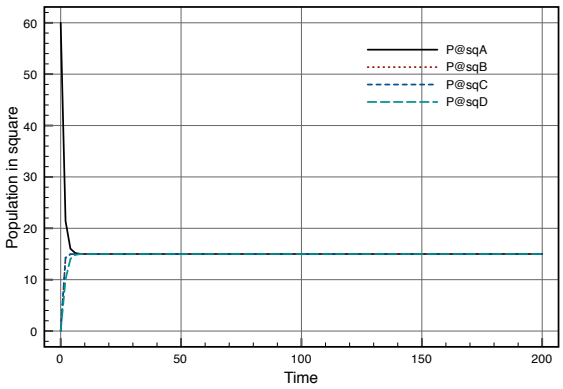
Figure 2(c) shows the results of stochastic simulation for the same model, but for $c = 0.10$, a value above the threshold. Corresponding fluid flow results for the same value of c are shown in Fig. 2(d). Besides the close correspondence between the stochastic simulation results and the fluid flow ones, the figures show that the population settles rather quickly in a steady state in which almost all agents remain in square A to chat with someone. This is the second type of steady state observed also by Rowe and Gomez.

Since these results show that both types of steady state emerge in this stochastic version of the crowd movement model and for both types of analysis, the question naturally arises whether fluid flow could be used as an efficient technique to investigate the behaviour of the model for various values of the chat-probability c, in particular those close to the critical threshold. To this purpose we have performed a fluid flow analysis for different chat probabilities ranging from 0.01 to 0.2 with steps of 0.01, except between 0.05 and 0.065 where the steps are 0.001. Each fluid flow analysis takes less than a second independently

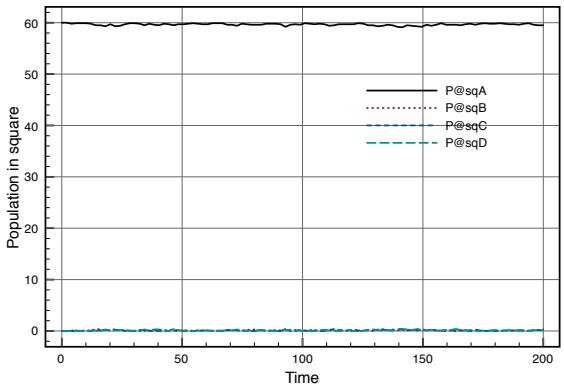
[3] All analyses have been performed with the Bio-PEPA Eclipse Plug-in tool [6] on a Macintosh PowerPC G5.



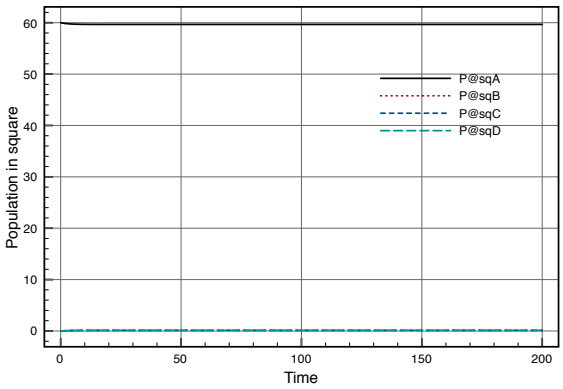
(a) Simulation results for c=0.005.



(b) Fluid flow results for c=0.005.



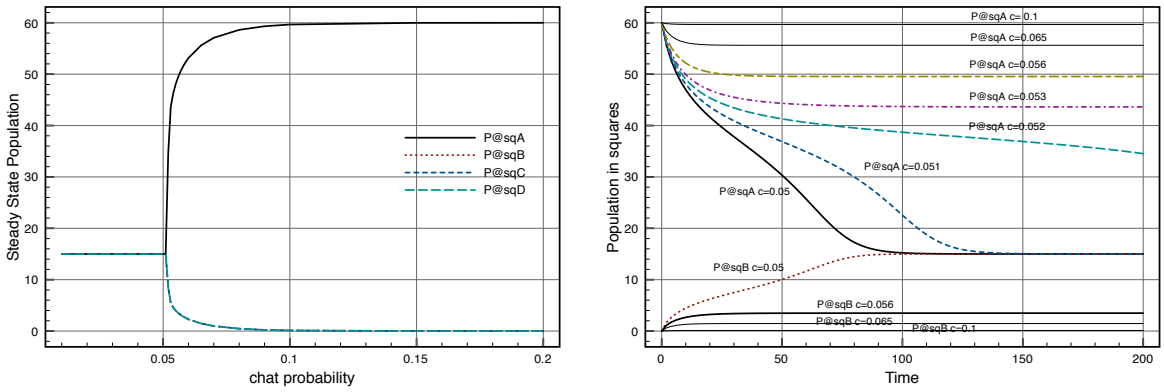
(c) Simulation results for c=0.10.



(d) Fluid flow results for c=0.10.

Figure 2: Results for four squares with 60 agents in A initially

of how many agents are considered in the model. If stochastic simulation would be used instead, the time for analysis would grow exponentially with the number of agents. The results are shown in Fig. 3(a) for the number of people in the squares on the long run (effectively at $t = 200$) starting with 60 people in square *A* initially. The figure shows clearly that for a chat probability below 0.05 in the steady state the population is evenly distributed over the four squares. For $c > 0.05$ the situation changes sharply. For these higher values of c the agent population tends to concentrate in square *A*, the square from which they started. All other squares remain essentially empty. The results in Fig. 3(a) show a clear case of spontaneous *self-organisation* or *emergent* behaviour. In other words, it shows the phenomenon that a structure or pattern appears in a system without being imposed by a central authority or any external element. Note that the results have been obtained by a series of numerical solutions of the ODEs derived from the Bio-PEPA model (fluid flow analysis) for various values of c instead of via stochastic simulation. The results in Fig. 3(a) closely correspond to those obtained by Rowe and Gomez [16] which have been obtained by discrete event simulation. The ease and efficiency with which these accurate results can be produced by means of fluid flow analysis opens up a promising perspective on how process algebraic fluid flow analysis could be used as an alternative, efficient, scalable and formal approach to investigate emergent behaviour in the vicinity of critical parameter values for this class of models.



(a) Steady state results for all squares.

(b) Fluid flow results for square A (and partially B) for varying chat probabilities around the critical value 0.05.

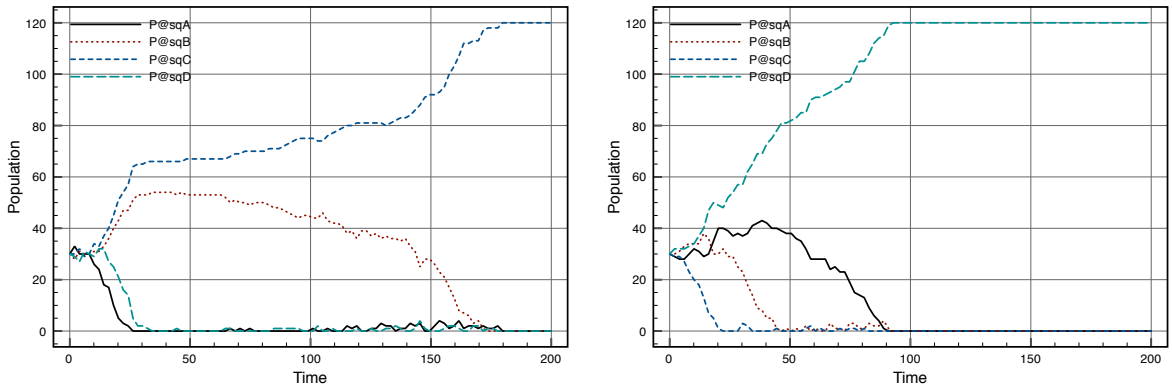
Figure 3: Steady state results at t=200 and varying chat probabilities.

An impression of how the distribution of agents over the four squares evolves for values of c that are close to the threshold of $c = 0.05$ is shown in Fig. 3(b). For $c = 0.05$ and $c = 0.051$ the agents still distribute uniformly over the four squares, though this takes a bit more time than for lower values of c. For $c = 0.052$ this situation is changing, and for $c = 0.053$ and higher clearly a different steady state is reached in which most agents group in the single square A. Note that for $c = 0.052$ a stable state has not yet been reached at time $t = 200$. However, this does not influence the overall picture.

Since the theory on the stability of fixed-points predicts that the steady state behaviour for values of $c > n/N = 4/60 = 0.066666$ is unstable (see [16]), we expect this to show up in the stochastic simulation and fluid approximation of our crowd model as well. Instability in this case means extreme sensitivity to the initial values of the number of agents in each square. In fact, simulation shows that the agents tend to gather in the square with the highest number of agents in the initial state. If the agents are initially distributed perfectly evenly over the squares, any of the four squares is equally likely to become the square where agents will gather in the long run. This is illustrated by the results in Fig. 4 where single simulation runs are shown for the same model starting with 30 agents in each square initially and for $c = 0.1$. Although so far we have considered models with a relatively low number of agents the the numerical approximation algorithms for ODEs are essentially insensitive in terms of efficiency to the size of the population considered as long as these populations are sufficiently large to guarantee sufficient precision. We have used 60 agents in this study to be able to compare our results with those obtained by Rowe and Gomez.

6 Conclusions and further work

The modelling and analysis of crowd dynamics appears to be an active and open research topic. We have explored the application of the stochastic process algebra Bio-PEPA to model a simple but interesting case study. This concerns the emergent self-organisation of parties in the squares of a city where people moving between squares are modelled as independently behaving agents following a few simple rules. Bio-PEPA is enhanced with various analysis techniques among which stochastic simulation, but in particular an efficient and scalable fluid flow approximation. Such an approximation provides a very efficient



(a) Simulation results for c=0.1.

(b) Simulation results for c=0.1.

Figure 4: Two single simulation runs for the same model with initially 30 agents in each square

method to obtain the average number of agents in a particular state over time. In the case study at hand fluid flow approximation provides an analysis of the number of people, on average, that are present in the various squares when time evolves. Although the simple topology addressed in this extended abstract can be analysed analytically, more complex topologies and models with squares with different levels of attractiveness do require a different approach in order to be feasible. Fluid flow approximation appears to be a suitable candidate (see also preliminary results about more complex models in [15], where squares are considered with different levels of attractiveness due to e.g. the presence of bars or open air events.)

We have shown how this approach can be used to investigate emergent behaviour that arises from the distributed local interaction between agents. The results are shown to correspond to those found in the literature where they were obtained by means of more elaborate and time-consuming discrete event simulation. The advantage of the fluid flow approximation with respect to simulation is that it is much faster than simulation if one is interested in the average behaviour of a system over time. Furthermore, Bio-PEPA is based on a modular, high-level language providing notions of locality and context dependency. These features make Bio-PEPA a promising candidate for the modelling of a class of systems that goes beyond the bio-molecular applications it was originally designed for [4, 9, 2].

Future work is developing along a few main directions. We are interested in developing further linguistic abstractions to more precisely describe the dynamics of systems with a large number of mobile agents displaced in a, possibly open, physical environment. We are furthermore interested in conducting more fundamental research on the fluid flow approach and its relationship to emergent non-linear behaviour, in particular its relation to mean field analysis [5].

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