Modeling Swarming Process for Systems of Unmanned Vehicles

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Abstract: - This paper substantiates and implements a novel concept for modeling the motion and interaction of a system of unmanned vehicles with varying functionality based on a mathematical description of swarming and aggregation in dispersed systems. The paper's novelty and contribution to the problem lies in its use of a stochastic lattice model (SLM) developed by the authors. Software was also developed, and a numerical experiment was conducted using the computer code demonstrating the capabilities of the new model. Key code fragments and illustrative results of numerical experiments have been submitted.

Key-Words: - Unmanned vehicles, swarming, multibodies collision, stochastic lattice model, cluster formation.

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1 Introduction

In the present time the issues related to controlling swarms of unmanned vehicles (UVs) of various types, including ground-based ones, acquired obvious relevance and significance, [1], [2], [3]. However, despite the existing works, this problem as a whole is not given enough attention, [4]. The theoretical analysis of many issues remains underdeveloped, [5], [6].

The authors believe that mathematical models of swarming and aggregation in dispersed systems can be applied to develop theoretical foundations for unmanned vehicles swarm control, [7], [8]. This paper attempts to construct such a model based on this theoretical framework, [9], [10].

It is known that swarming and the formation of aggregated clusters play a decisive role in systems of moving objects of various nature, [11], [12], [13]. A comprehensive review of theoretical models of aggregation processes in dispersed systems is given in the work by Wattis, [14].

Despite numerous publications, two main models remain the most popular. They are the Smoluchowski equations and the Becker-Döring model, [14], [15]. Both of these models are based on the assumption of binary collisions. Models allowing for multiparticle collisions have not been developed into algorithms which are convenient for real-world calculations. The assumption of the prevalence of binary collisions has some justification in sparse systems, when the probability of multi-particle collisions is significantly lower than the probability of binary collisions. However, this assumption ceases to be justified for concentrated dispersed systems, [16].

The corresponding estimates for the applicability limits of the binary collision model are obtained in the work [15]. An asymptotic analysis shows that the assumption that frequency of pairwise collisions always strongly predominate over frequency of multibodies collisions is not correct. It has been shown that the contribution of multibodies collisions to the rate of formation of localized regions of increased particles density in a swarm can be comparable to the contribution of binary collisions for dense dispersed systems, [17], [18].

Below is a brief overview of these issues, taking into account possible interactions—collisions—of UVs in a swarm.

For describing swarming processes in unmanned vehicles streams, the sparse dispersion model is in most cases not applicable, since a swarm of unmanned devices, regardless of their functionality, moves along a given trajectory and within a certain specified deviation from this trajectory, [19]. However, in our opinion, beyond the limitation of binary collisions alone, other considerations limiting the correct application of the aforementioned models are also important, [20], [21].

It should be noted that models based on the Smoluchowski and Becker-Döring equations do not assume the simultaneous formation of dense clusters (aggregates) and swarming, i.e., the movement of dispersion in localized regions (swarms). Thus, both the Smoluchowski and Becker-Döring equations are not designed to describe swarming and aggregation processes, not only in dense dispersions, but also in the presence of significant gradients of particle concentration in the region of swarm movement, [22], [23].

This aspect of the problem is that the dispersion density can be distributed non-uniformly in the space in which the swarm of unmanned vehicles moves, and the movement of such a swarm can be accompanied by the formation of localized regions of increased density—clusters, [24]. Such local non-uniformity can vary significantly in time and space, [25].

At the same time, a review of the literature published to date failed to find any works proposing well-founded mathematical models for describing aggregation and swarming processes in spatially heterogeneous complex dispersed moving systems, [20], [26]. Such models would have to consist of systems of partial differential equations, unlike to the Smoluchowski or Becker-Döring models. However, absence of similar models precludes correct analytical study of swarm structuring and stabilization. The use of Fokker-Plank type equations [27] for these issues may turn out to be promising. However, this problem becomes open today, [28].

In this paper, the authors do not set the task of deriving such models. The problem is considered from an algorithmic perspective only. Thus, the paper devotes to investigation of possibilities of the stochastic lattice model (SLM) application, previously developed and proposed by the authors [9], to describe the processes of swarming and aggregation in streams of moving unmanned vehicles. The main attention is paid to the description of the concept and algorithm for numerical calculation of the processes of swarming and aggregation of moving objects using the SLM model.

The region in which swarming and clustering processes occur is covered by a fixed spatial lattice. Then, the change in the local distribution of regions of varying density as clusters of varying orders in the cells of the resulting lattice is then described, [9]. With this approach, the kinetically competing processes of swarming and clustering [29] in an external force field, if one exists, are essentially described from a unified perspective.

Therefore, unlike previous SLM model-based studies, the ability to account for the influence of external control actions on devices movement (called in the paper as drift across the lattice) is provided. This difference may be crucial for swarm control strategies, [30].

2 Problem Formulation

The new model considers two different types of cluster formation for vehicles moving on a lattice.

The first type is "fast" cluster formation, when two or more vehicles, after entering one common cell, they move further across the lattice as a single cluster. This type of clustering corresponds to the so-called diffusion-limited aggregation (DLA) in kinetic theory, [31].

The second type of clustering does not involve the obligatory formation of a single cluster of objects immediately after the first simultaneous entry into a common cell. According to this model case, with “slow” clustering it is assumed that the formation of a cluster is completed only after the secondary joint movement of a group of objects to the next cell of the lattice. In the second case, the direction of movement (drift) from the cell is randomly chosen for each cluster within it. Then, joint movement along the same route is interpreted as the emergence of a connection, that is the formation of a common cluster. This type of clustering in SLM model corresponds to the so-called mixed aggregation in kinetic theory, [14]. Applying to the movement of unmanned vehicles, such a case may describe the presence of a one-time external control action.

The model describes a three-dimensional domain and assumes vehicle drift in both horizontal and vertical directions (going up or down the slope of a hill, for example). To construct a three-dimensional modeling algorithm, a third parameter—depth—was added to the algorithm for the two-dimensional case.

In this paper, the simulation is performed in the conditional space of a stochastic lattice of given scales. Therefore, the contractual unit of measurement for spatial displacement—drift—is the size of a stochastic lattice cell. Thus, a drift of one unit to the left, right, up, or down represents a transition to an adjacent cell. Drift can also occur through several cells.

For consistency of terminology, when referring to swarming and aggregation models, UVs localized in the cells of a stochastic lattice will be called particles or, in the case of aggregates of many objects, clusters.

Three modes of initial particle positions are proposed:
1) all lattice cells are filled with particles;
2) the particles in the lattice are staggered;
3) The particles form a square region.

The input parameters of the model under consideration are:
1) At the initial state each cell contains one particle of order 1. Then, at the first step, the horizontal and vertical velocity components of the drift are selected from the sample (-3; -2; -1; 0; 1; 2; 3).
2) Then, at each next step, the horizontal and vertical velocity components of the drift are selected according to the following principle: for clusters of order 1, from the sample (-3; -2; -1; 0; 1; 2; 3); for clusters of order 2, from the sample (-3; -2; -2; -1; -1; 0; 1; 1; 2; 2; 3); for clusters of order 3, from the sample (-2; -1; -1; 0; 1; 1; 2); for clusters of order 4 - (-2; -1; -1; -1; 0; 1; 1; 1; 2); for clusters of order greater than 4 - (-1; -1; 0; 0; 1; 1).

Such samples are adopted in order to modeling the decrease in particle mobility with increasing order. Of course, this choice is arbitrary and it is used to demonstrate the concept itself. In any given real-world situation, the choice of drift size will be determined especially.
3) For the model implementation of the second type of clustering, each cell of the lattice is divided into 7 sub-cells to place particles into these sub-cells that do not form a common cluster immediately after entering the common cell. A numerical experiment showed that, given the adopted drift samples, seven such sub-cells were sufficient.

For the obtained local compounds, the types and orders of clusters formed can be determined using the mathematical apparatus of random walk and collisions in mathematical lattices.

3 Problem Solution

The algorithmic approach to describing swarming and clusterization processes for the swarm of unmanned vehicles is generally consistent with the discrete-event modeling (DEM) paradigm. This apparatus allows for solving the problem by taking into account the influence of multibodies collisions and, without significantly complicating the model, and allows also for describing both drift-limited aggregation and the competition between different mechanisms occurring at different characteristic stages. The algorithm is designed to generate and conduct two numerical experiments for two types of clustering.

Considerations for deriving formulas for cases of fast and slow cluster formation are illustrated in Figure 1 - A) and B), respectively.

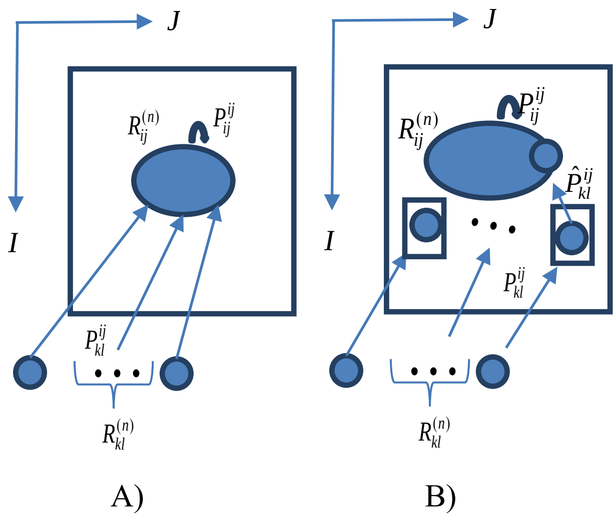

Fig.1: A)- To the derivation of relation (1) for calculating the change in cluster order in one step during “fast” cluster formation (similar to DLA aggregation); B)- To the derivation of relation (2) for calculating the change in cluster order in one step during “slow” cluster formation (similar to mixed kinetic aggregation).
Source: created by the authors

The following is the derivation of the formulas for the number of clusters in a cell with indices (i, j) per unit of time can be written as follows.

In the case of fast cluster formation, the number of clusters entering the common cell is equal to the order of a forming cluster.

$$M\left(R_{ij}^{(n+1)}\right) = -R_{ij}^{(n)}\left(1 - P_{ij}^{ij}\right) + \sum_{k}\sum_{l} R_{kl}^{(n)} P_{kl}^{ij} \qquad (1)$$

The corresponding equation for the case of slow cluster formation when it is necessary to take into account not only drift-limited, but also possible other mechanisms of UVs localization, due to the swarm control paradigm, looks like this:

$$M\left(R_{ij}^{(n+1)}\right) = -R_{ij}^{(n)}\left(1 - P_{ij}^{ij}\right) + \sum_{k}\sum_{l} R_{kl}^{(n)} P_{kl}^{ij} \hat{P}_{kl}^{ij} \qquad (2)$$

Here:
M is the symbol of mathematical expectation;
P_{kl}^{ij} is the probability of the vehicle drift from the cell (i, j) to the cell (k, l);
$R_{ij}^{(n)}$ - is the cluster order in the cell (i, j) at the time step # n;
$R_{kl}^{(n)}$ - is the cluster order in the cell (k, l) at the time step # n;

P_{ij}^{ij} - is the probability of that the cluster will not leave the current cell in the next step.

$1-P_{ij}^{ij}$ - is the complete probability of exiting of the cluster from the cell at given time step;

$\hat{P}_{kl}^{ij}$ is the probability of subsequent combined movement (i.e., with accounting the possible external action) of a cluster moving from cell (*k*,*l*) to cell (*i*,*j*).

The described procedures are presented in Figure 2. The first shaded columns of the matrix W indicate the region occupied by the stream of particles arriving during a unit of time into the described area.

According to the above scheme, random displacements were selected for each particle, and then the particles can have aggregated.

This process was then repeated at each time step. Numerical experiments were performed on matrices of dimensions 4x40, 8x40, 5x20, and 4x100, which simulated the areas of particles stream with lengths of 20, 40, and 100 cells and widths of 4, 5, and 8 cells.

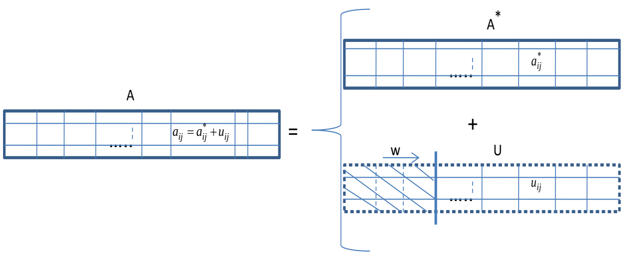

Fig. 2: Schematic of the calculation procedure
Source:[9]

Calculation scheme for the case of mixed mechanism of clusters formation looks like this.

The algorithm is designed so to find multiple unaggregated clusters in a single cell at different time units. In order to solving this problem, five three-dimensional arrays should be created.

The arrays *A* (first), *U* (second), and *A** (third) are defined according the scheme in Figure 2. The fourth array, *S*, represents the number of particle collisions in each cell in each unit of time.

A fifth array $B(i, j, m)$ is also generated. It serves as an identifier of the previous cell from which the given cluster moves to the new cell. Here, (*i*, *j*) is the indices of the cells into which the cluster enters in given time interval, and the third index, m, is the label of the cell in which the cluster was before the start of the movement.

$$m=(i-1)N+j, \quad (3)$$

where N – the number of the matrix columns.

This algorithm allows us to identify clusters with identical labels, which will be aggregated according to the proposed model in the case of slow cluster formation. Thus, array *B* acts as an array-witness of aggregation. Clusters with different labels continue to migrate separately.

The main application object is launched on program startup. It implements the system's core functions. Interaction with other application objects is accomplished through a menu element (TMainMenu) and a button panel (TActionPanel, TSpeedButton). The menu structure is managed by a component (TAction).

Navigation through departments and computers is accomplished using the TreeView component, which displays all project components in a tree structure.

The right side of the window displays information about departments or computers (depending on the selected level in the TTreeView component). The information is displayed as a tabbed element (Pagecontrol).

Each tab displays information from the database. The Tedit, TMemo, TLookupCombobox, and TGrid components display and edit information. The Tbitbtn buttons are used to add, edit, and delete elements. Panels and form labels (TPanel, TLabel, TGroupButton) perform interface functions only. Category navigation is accomplished using the TTreeView component, which displays component categories in a tree structure.

After launching, the application's main window appears (Figure 3), consisting of a top menu and a workspace with document packages where you can view data and experiment results:

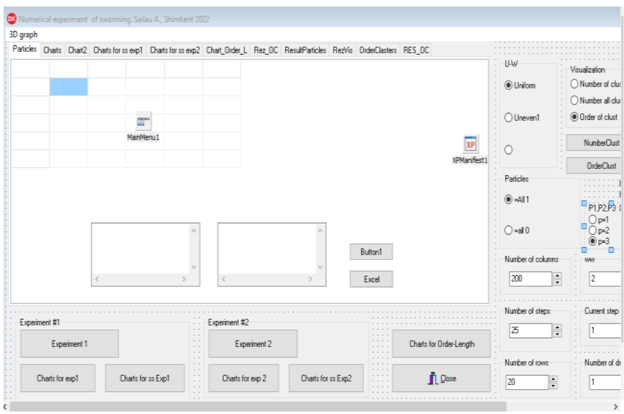

Fig. 3: The main application window
Source: created by the authors

4 Numerical Experiment Description and Discussion

The numerical experiment utilized the idea of array swapping: the initial array (for a motion with possible stops, this is the first array; for a continuous movement, these are the first and second arrays) and the future array (for periodic stops, this is the third array; for a continuous movement, these are the fourth and fifth arrays).

As described above, the initial array values are transformed into the future array values using specific algorithms. This process is controlled by a specified cycle number.

The experimental computational scheme consists of initial computational procedures, a particle velocity calculation, particle motion direction choice, calculation of the number and order of clusters over time, generation of the number and order of clusters over time, and output of all calculations to a file.

The particle velocity calculation is determined by the Tform1.vel procedure. Figure 4, Figure 5, Figure 6 depict the main fragments of the appropriate code.

```
procedure Tform1.nach;
  var i,j,l,step,sU,ng,nv,k:Integer;
  col_v,col_g:extended;
begin

  //v 2 4 8 10
w1:=strtoint(ew.text);
   //n1 5*20 4*40 4*100 8*40
ix:=0;
n1:=strtoint(edit1.text);
n2:=strtoint(col.text);
n3:=strtoint(edit2.text);

rezPart.ColCount:=n2+1;
rezPart.RowCount:=500;

rezVis.ColCount:=n2+1;
rezVis.RowCount:=500;

oc.ColCount:=n2+1;
oc.RowCount:=500;

Rezoc.ColCount:=n2+1;
Rezoc.RowCount:=500;
```

Fig. 4: Input of initial data for the calculation procedure
Source: created by the authors

```
procedure Tform1.velW;

 var s1,s4,i,j,l:Integer;

begin
for l:=1 to n2 do
for i:=1 to n1 do
for j:=1 to n3 do
begin
 vgW[l,i,j]:=0;  vvW[l,i,j]:=0; vfW[l,i,j]:=0;
end;

for l:=1 to n2 do
for i:=1 to n1 do
for j:=1 to n3 do
begin

 if U[l,i,j]<>0 then
 begin
    randomR;

  if U[l,i,j]=1 then
  vgW[l,i,j]:=Rnumbers_1[Rn_1];
  if U[l,i,j]=2 then
  vgW[l,i,j]:=Rnumbers_2[Rn_2];
  if U[l,i,j]=3 then
  vgW[l,i,j]:=Rnumbers_3[Rn_3];
  if U[l,i,j]=4 then
  vgW[l,i,j]:=Rnumbers_4[Rn_4];
```

Fig. 5: Calculating Particle Velocity Procedure. Excerpt from the code
Source: created by the authors

```
calcvg;
if ((st mod 1)=0) then
begin

calcNumbers;

    lp:=40;//40
    ip:=4;
    ix:=ix+1;
     li:=0;
  while (lp*li+lp<=n2)  do
  begin

   for j:=1 to n3 do    //for l:=lp*li+1 to lp*li+lp do
   begin
       ii:=0;   sum_ch1:=0; sum_kol1:=0;
 for i1:=1 to ip do
  begin

    for l:=lp*li+1 to lp*li+lp do
  //
        begin

          if vis.ItemIndex=0 then begin
           if ch[l,i,j]=1 then col1V1:=col1V1+1;
           if ch[l,i,j]=2 then col2V1:=col2V1+1;
           if ch[l,i,j]=3 then col3V1:=col3V1+1;
           if ch[l,i,j]=4 then col4V1:=col4V1+1;
           if ch[l,i,j]=5 then col5V1:=col5V1+1;
```

Fig. 6: A fragment of the procedure for outputting calculated data to a file
Source: created by the authors

The results of a study using the developed model demonstrated that an algorithmic approach based on the DES paradigm can be effectively used to calculate the kinetics of migration processes for various types of unmanned vehicles, taking into account the non-uniform flow distribution of such vehicles and the formation of swarms and clusters of co-moving vehicles. This mathematical tool eliminates the problems associated with accounting for the influence of multi-body interactions and offers methods for describing the structure of unmanned vehicle swarms for cases of fast and slow cluster formation, accounting for competition between various kinetic mechanisms occurring at different characteristic points in time.

Figure 7 shows an example of a window displaying the results of a numerical experiment.

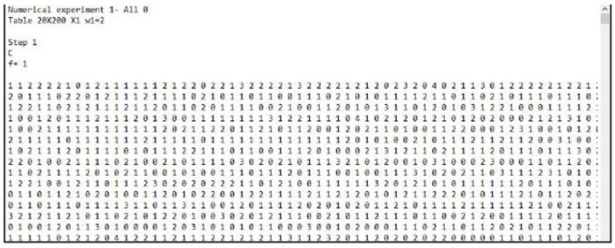

Fig. 7: An experiment results example
Source: created by the authors

The numbers in Figure 7 indicate the orders of particle clusters in the lattice cells. Since the number of particles in the lattice cells and the cluster orders (i.e., the number of grouped aggregated particles) do not coincide during slow cluster formation, these data were displayed separately during the numerical experiment. Figure 8 and Figure 9 display these results using different depths of color tones for the lattice cells with different particles number and different sum of clusters orders.

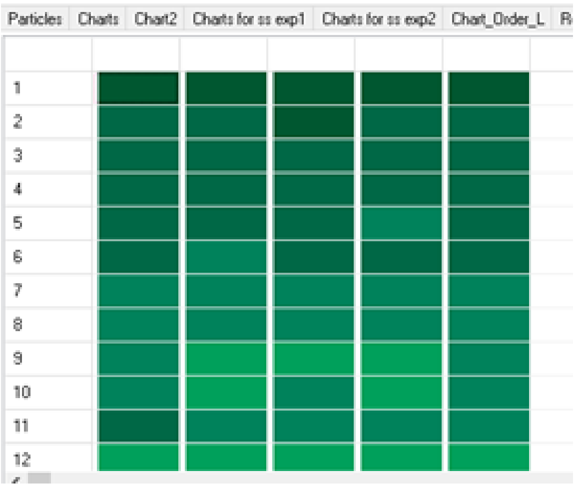

Fig. 8: Results of calculating the total numbers of single vehicles in different cells
Source: created by the authors

The numerical study demonstrated that the contribution of simultaneous interactions of multiple cluster particles in dense systems to clustering kinetics is quite significant and can reach 25 percent or more, especially at an early stage of the process.

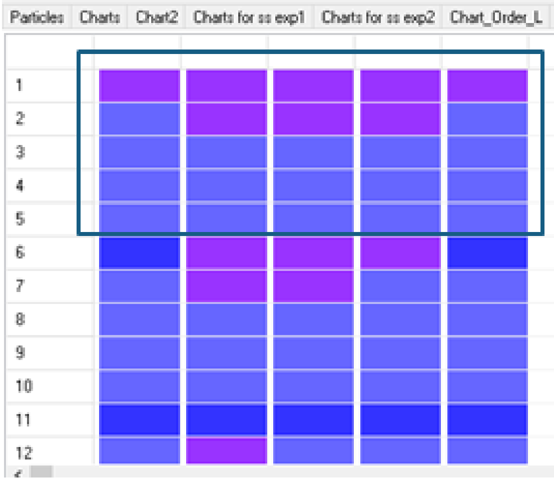

Fig. 9: Results of calculating the sum of cluster orders in different cells
Source: created by the authors

This result confirms doubts about the possibility of correct using equations based on the hypothesis of the predominance of binary interactions for dense dispersed systems. Thus, it is impossible to accurately compare the obtained results with those calculated using the Smoluchowski or Becker-Döring models. This is due the fact that the control parameters of these models are also random functions, but, unlike the stochastic lattice model, there is no standard form for these random functions. At the same time, in the calculation algorithm according to the stochastic lattice model, the probabilities of random drifts are explicitly present. Besides, the important feature of the modified algorithm is the ability to describe the influence of one unmanned vehicle as an attractor on the drift of other vehicles, which is modeled by the predominance of the probability of transition from a given cell to an adjacent lattice cell located close to the attractor, [21].

However, the results of the numerical experiment described should be considered qualitative. They are not intended to provide any quantitative recommendations. The primary purpose is to discuss the capabilities and advantages of the new model.

5 Conclusion

The results of the conducted research confirm that the stochastic lattice model can be effectively used for mathematical modeling of unmanned vehicles (UVs) swarm movements. Two main cases are considered: cases of rapid and slow formation of UVs clusters within the swarm. Probabilistic novel formulas for calculating UVs concentrations within the swarm are proposed, and software is developed that could prove useful for creating a UVs swarm control system.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Sabira Akhmetova carried out the simulation, Arnold Brener proposed a concept for constructing the model, Serik Ismailov and Amantay Batyrbekov have implemented the algorithm and soft for numerical experiment, Aliya Ismailova has organized and executed the experiments.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.