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# A stigmergic algorithm for solving inverse thermal systems

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**A stigmergic algorithm for solving inverse thermal systems**

by

**Peter Samuel Broen Finzell**

A thesis submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Mechanical Engineering

Program of Study Committee:  
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Ames, Iowa

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## ABSTRACT

This thesis proposes a novel method for solving inverse thermal systems problems based on stigmergy. Inverse problems are those problems that have a desired output but the inputs required to achieve that output are unknown. The example problem examined is an established inverse radiation heat transfer problem in which two parallel plates are separated by a distance. The temperature profile along the top plate is adjusted to achieve a specified temperature profile on the insulated bottom plate. This type of inverse radiation problem arises in annealing, industrial process ovens, and combustion chambers. Stigmergic processes rely on local instructions and interactions and as a result can be readily scaled up to larger and more complex systems. The algorithm developed here uses the concept of distributed construction and finds the solution without direct communication and uses only local information. Specifically, a stigmergic algorithm was developed based on the egg dumping and redistribution behavior of lacebugs (*Gargaphia solani*) and the construction of ant cemeteries based on ant species *Lasius niger* and *Pheidole pallidula*. The algorithm is demonstrated with five separate lower surface starting and ending profiles. In contrast with traditional methods that rely on global information, the desired temperature profiles are attained using only local information. Based on this, in each case the temperature profile of the lower surface rapidly converges to the desired temperature profile. Therefore, sensors can be added as needed without restructuring the sensors network or control strategy.

## CHAPTER 1. INTRODUCTION

Energy systems are becoming increasingly complex and require better control to meet increasingly stringent environmental regulations. Normally, the goal of these energy systems is to adjust a set of control protocols to achieve or maintain a specific set of outputs. These types of problems are considered inverse problems, when the desired output is known and the inputs are not known. Inverse problems are considered ill-posed and are challenging because solutions can be difficult to attain, and when one is found it may be infeasible based on constraints.

When written explicitly, inverse problems cannot be solved directly using traditional analytical techniques. Regularization or optimization are typical means of solving these problems. Regularization filters out the ill-condition part of the problem such that stable solutions can be found. Optimization problems form some objective function that specifies boundary conditions. An optimization routine is run over multiple iterations such that better solutions are found that continue to minimize the objective function until some stopping criteria is met (Duan 2005).

This thesis presents a novel method to solve inverse thermal systems based on the coordination behavior of social insects' ability to construct complex structures using only local information. These social insects act as autonomous agents, capable of building complex structures using cues from their environment as a means of coordination. This coordination, which is based solely on the manipulation of their environment, is called stigmergy. Stigmergy is based on the concept of emergence, where global behavior is created from local interactions, coordinated by the manipulation of the environment. It is this

coordination through environmental interaction that allows a system to become more robust and flexible, and it is this characteristic that is desirable in finding a new method to find a solution to an inverse thermal systems problem.

## CHAPTER 2. BACKGROUND

Dynamic energy systems are typically driven by sensors which are distributed throughout the system to gauge the behavior and responses of the system outputs. These systems make decisions based on some control scheme while trying to achieve some optimal conditions. Centralized control, while preferred because of simplicity, becomes increasingly difficult to coordinate as the size and complexity of both the sensor network and the system being controlled increase. This creates a need for a different control paradigm, one in which top-down centralized controllers are replaced by a flexible, robust, and scalable network of sensors and controllers, and with the capability of self-organizing, allow control decisions to be made at the local level rather than passed upwards through some hierarchy.

With distributed control, each sensor is able to make control decisions independently, based on local information, thus allowing the system to be more scalable and flexible (Dressler, Krüger, and Fuchs 2005). Decentralization minimizes the amount of decisions any one sensor needs to make at any one time and allows each sensor to become an autonomous agent capable of making decisions without a centralized controller giving instructions. This same concept of decentralization helps explain the emergent, self-organized behavior in social insects.

### **2.1 Self-Organization, Emergence and Stigmergy**

Self-organization draws its origins in biological systems and establishes how organisms can react, adapt, and interact with their environment and each other to create macroscopic level behaviors from microscopic interactions (Halley and Winkler 2008).

Flocking behavior of birds and schooling behavior of fish are both examples of how order can spontaneously be created from disorder and how global behaviors are created from local interactions (Camazine et al. 2003). Based on this concept of emergence, where patterns and structures are created spontaneously without a template, step-by-step instructions, or global information, self-organization has been shown to be a useful tool in complex distributed systems.

Stigmergy is based on indirect communication methods used by social insects for coordination of behaviors. Stigmergy, like self-organization, uses local information to make decision and has no step-by-step instructions. Coordination is established by making small changes to the insects' environment which other insects can interpret triggering actions or responses further altering their environment (Bonabeau et al. 1997). Actions reinforce each other and can lead to the spontaneous emergence of complex, intelligent structures without the need for centralized planning, control, or direct communication between the individuals.

Jean Louis Deneubourg sought to answer the question of how ants can build such complex structures from only local information. He noted that their behavior was based on pheromones, both those left on the ground for foraging or those impregnated into soil for nest construction. When foraging, ants make decisions about where to go based on a pheromone trail, but this pheromone trail strength was based on how many ants used a trail and how frequently they used it (Deneubourg et al. 1990; Goss et al. 1990). Increased use reinforces and strengthens the pheromone trail, but if the trail is used infrequently the pheromones evaporate and the pheromone trail weakens.

There are two types of stigmergy: quantitative and qualitative stigmergy. Quantitative stigmergy is a homogenous stimulus, whereas qualitative stigmergy is a discrete set of non-

homogenous stimuli (Theraulaz and Bonobea 1999). Qualitative stigmergy can be thought of as how termites construct pillars for their nest construction. There is an identical pheromone that is built up over time and when a threshold is reached, an action is performed. This takes place in two phases, which are non-coordinated and coordinated. In the non-coordinated phase some action is performed, such as impregnating soil pellets with pheromones, as the termites collect the pellets. Once the threshold pheromone level is reached, the coordinated or action stage begins. This action stage leads to the creation of termite pillars, and as the pillars are constructed, the pheromone level drops down and the coordinated stage stops (Theraulaz, Bonabeau, and Deneubourg 1998). An example of qualitative sign-based stigmergy is the dance that bees use when communicating to the rest of the hive after a foraging trip. If a resource is nearby and plentiful, the bee will perform a specific, intricate dance, communicating the specific direction and distance to and from the resource with different dance movements (Frisch 1967).

## **2.2 Inverse Radiation Heat Transfer Problems**

To determine the temperature or heat flux distribution over one or more surfaces, the solution set becomes very sensitive to errors. The ill-posed nature of heat transfer problems leads them to be estimations rather than exact answers. Typically inverse heat transfer problems (IHTP) use a regularization or optimization to find a solution to problems that would otherwise be too time consuming to compute analytical solutions. Inverse heat transfer problems can be solved using either parameter estimation or function estimation. Using parameter estimation, a set of conditions is estimated. Using function estimation, a function is estimated and the conditions are solved for (Beck, Blackwell, and St. Clair 1985).

Regularization techniques, such as truncated singular value decomposition, modified truncated singular value decomposition, and Tikhonov regularization have been used to solve IHTP problems using different geometric configurations and initial conditions which are discussed in (Rukolaine 2007; Daun et al. 2006; Ertürk, Ezekoye, and Howell 2002a). Optimization techniques such as conjugate gradient (Park and Yoon 2000) and genetic algorithms (Amiri et al. 2011; Safavinejad et al. 2009), tabu search and simulated annealing (Porter et al. 2006) and a quasi-Newton method (Daun, Howell, and Morton 2004) have been used to find heater temperature settings for transient systems. Ertürk used artificial neural networks to solve an IHTP (Ertürk, Ezekoye, and Howell 2002c). Yang was able to control the temperature of an oven during runtime using genetic algorithms (Yang, Chan, and Luo 2005). On-line genetic algorithms were used to control the proportional and integral gain values of a heating system (Ahmad, Zhang, and Readle 1997).

Control of distributed thermal systems in rapid thermal processing (RPT) has a wide array of applications in semiconductor, metal and glass cooling, and many other manufacturing industries that require precise control of multiple heaters to achieve a uniform temperature across the product. There is an increase in demand for temperature uniformity and the ability to hold that temperature at a steady state precisely as long as needed for the manufacturing process (Dassau, Grosman, and Lewin 2006; Emami-Naeini et al. 2003; Balakrishnan and Edgar 2000; Yoshitani and Hasegawa 1998; Young Man Cho and Gyugyi 1997; Schaper 1994). Rapid thermal prototyping is concerned with an actual process for maintaining a uniform surface temperature of an inverse radiant system but uses more conventional control techniques such as adaptive control and linear quadratic Gaussian control (Lee et al. 2001) and PID tuning (Dassau, Grosman, and Lewin 2006).

## CHAPTER 3. DISTRIBUTED CONSTRUCTION APPLIED TO AN INVERSE HEAT TRANSFER PROBLEM

A paper to be submitted in *Advances in Engineering Software*

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### **Abstract**

Engineering problems that specify output conditions but require a given input are considered ill-posed. This paper focuses on creating a stigmergic algorithm to solve an inverse radiation heat transfer problem. This stigmergic algorithm is inspired by the egg dumping and redistribution behavior of lacebugs (*Gargaphia solani*) and the construction of ant cemeteries based on *Lasius niger* and *Pheidole pallidula*. Five separate trials were performed to gauge the effectiveness of the algorithm at achieving a uniform or varied temperature distribution from different initial conditions. The stigmergic algorithm was shown to be capable of achieving the desired temperature profiles to within an acceptable degree of accuracy.

### **Key Words:**

Inverse problems; Radiation heat transfer; Stigmergy; Self-organization; Distributed construction

### 3.1 Introduction

This paper presents a novel solution strategy for inverse thermal system problems using distributed construction. In distributed construction, autonomous agents use only local information and simple interactions to solve construction problems based on emergent behavior. Emergent behavior is created from the bottom up; order and structure emerge spontaneously and organically (White 2005). Using only local information, patterns and structure begin to emerge from the agent's interactions without a predefined map or plan (Bonabeau et al. 2000). The concept of distributed construction is inspired by the stigmergic processes used by social insects, (termites, bees, ants and wasps) to coordinate their behavior to build complex structures using only the environment as a means of coordination. As changes are made to an environment, either through pheromone deposition or gradual construction, agents can interpret those cues and contribute. Every agent's action is made independent of another agent's, thus allowing the whole coordination to be distributed among any number of agents. Additional agents can contribute if needed or leave without consequence, allowing these systems to be distributed, robust, and scalable.

Distributed construction has been used to examine the applicability of stigmergic processes to the construction of complex two- and three-dimensional structures and lattices using simple blocks (Petersen, Nagpal, and Werfel, 2011). Theraulaz et al. used stigmergy to replicate the distributed construction behavior of paper wasps and was able to create three dimensional lattice structures using simple building blocks (Theraulaz and Bonabeau 1995).

These autonomous agents can be thought of as mobile platforms guided by sensors. An instance of this is a power plant, which uses a network of sensors and actuators that can

be adjusted to maintain a particular configuration (e.g., a given power and emissions level). The sensors are the autonomous agents, using the information available locally to make decisions in order to reach and maintain the particular configuration. The concept of distributed construction can be extended to other domains. In thermal systems, the agents are static and the structure being constructed is the establishment of specific thermal conditions.

This paper first develops the concept and then demonstrates the concept using the established ill-posed parallel plate radiation heat transfer problem (Namjoo et al. 2009; Zhou et al. 2002; França et al. 2002; Morales 1998). With traditional heat transfer the conditions or parameters are fully specified and the outcome is solved for. With inverse problems, the desired outcome is specified and the conditions that give the desired output need to be determined (Daun, Howell, and Morton 2003; Daun, Ertürk, and Howell 2002; Ertürk, Ezekoye, and Howell 2002b; Beck, Blackwell, and St. Clair 1985). This problem consists of two parallel plates separated by some distance and with radiation heat transfer from the top surfaces to the bottom surfaces. The top surface temperatures are set such that the lower temperature is maintained at a desired temperature via radiation transfer. Distributed construction can be thought of as an inverse problem as well because the desired final structure is specified, and the collective behavior to produce that structure needs to be found. Thus, the same concepts that have been used to solve distributed construction problems will be applied to an inverse thermal problem. Although distributed construction is the encompassing idea, two stigmergic insect behaviors inspired pieces of this algorithm.

### 3.1.1 Cemetery Construction and Egg Dumping

When ants in a colony die they generally die in the middle of whatever task they were performing. This can be an inconvenience for the other ants trying to work around them. The *Lasius niger* or *Pheidole pallidula* ants clear out their dead to make more room by clustering the corpses into larger and larger piles. This is done without prior knowledge of where the piles will form or which piles will become the largest. This takes place in two phases, non-coordinated and coordinated. In the non-coordinated stage, each dead ant acts as a stimulus and, once a threshold of corpses is reached, worker ants take action by sorting them into clusters. As these cluster become larger, the stimulus for removing the dead decreases until there are only several large clusters of dead workers (Bonabeau, Dorigo, and Theraulaz 1999; Deneubourg, Goss, and Franks 1991). This behavior has been replicated by computational (Tsankova and Georgieva 2004; Jones and Matarić 2003) and physical agents (Phan and Rusell 2012; Parker and Zhang 2011; Beckers, Holland and Deneubourg 1994).

Ants, termites, wasps, and bees are eusocial, wherein members of the same generation live together with “cooperative care”, and there is a reproductive division of labor; however other social insects are considered communal, meaning members of the same generation live together. Parental care in insect societies is relatively rare, and communal care is a rarer subset (Costa 2006). Most of these communal insect societies deposit eggs individually and guard them against predation and against others in the community. There exists an even smaller number of insect species that exhibit not only communal care but also egg dumping or sharing behavior. Example insect species include barklice, *Peripsocus nitens*; lacebugs *Gargaphia solani*; and treehoppers *Publilia concava* and *Polyglypta dispar* (Tallamy 2005; Zink 2003). Egg dumping can be individually beneficial where dumping eggs in another

female's nest to increase the amount of offspring one female can produce in her lifetime or separately can be mutually beneficial. One of the best examples of mutually beneficial relationships in egg dumping is in the *Gargaphia solani* (Loeb and Zink 2006). Although egg dumpers are attracted to egg masses as long as one is available, at some point one will not be available and the females will be forced to lay and guard their own eggs. This female will accept eggs willingly, and as other females deposit their eggs in her egg mass, the probability that her own eggs will survive increases. She will continue to accept eggs until resources become too scarce, and she cannot accept any more. To maximize the number of their own offspring it is assumed there is an ideal brood size that each female seeks to attain. If it is too small, most will survive but not produce an ideal number of offspring, and if it is too large, their resources become scarce to the point that survival rate drops significantly. Finding an ideal brood size in order to optimize the survival rate is the main motivation for both dumpers and hosts.

### 3.2 Inverse Radiation Heat Transfer Problem

The problem examined is concern with two parallel plates separated by a certain distance with the top surface attempting to create and maintain a certain temperature profile along the lower surface. As shown in Fig. 3.1, if the top surface was assumed to be one uniform temperature, the temperature distribution along the lower surface would be higher in the middle and lower on the ends. In order to find a solution to this problem and create a uniform temperature distribution along the lower surface, the top plate will have to have different temperatures along several sub surfaces. Thus the top and bottom plates are each broken up into ten sub surfaces. The top surfaces can be thought of as the heaters. As each

heater is turned on, the radiative heat from that heater will affect all of the lower sub surfaces. The plate is discretized into sub surfaces and Fig. 3.1 shows the radiation heat transfer from each of the upper sub surfaces to each of the lower sub surfaces.

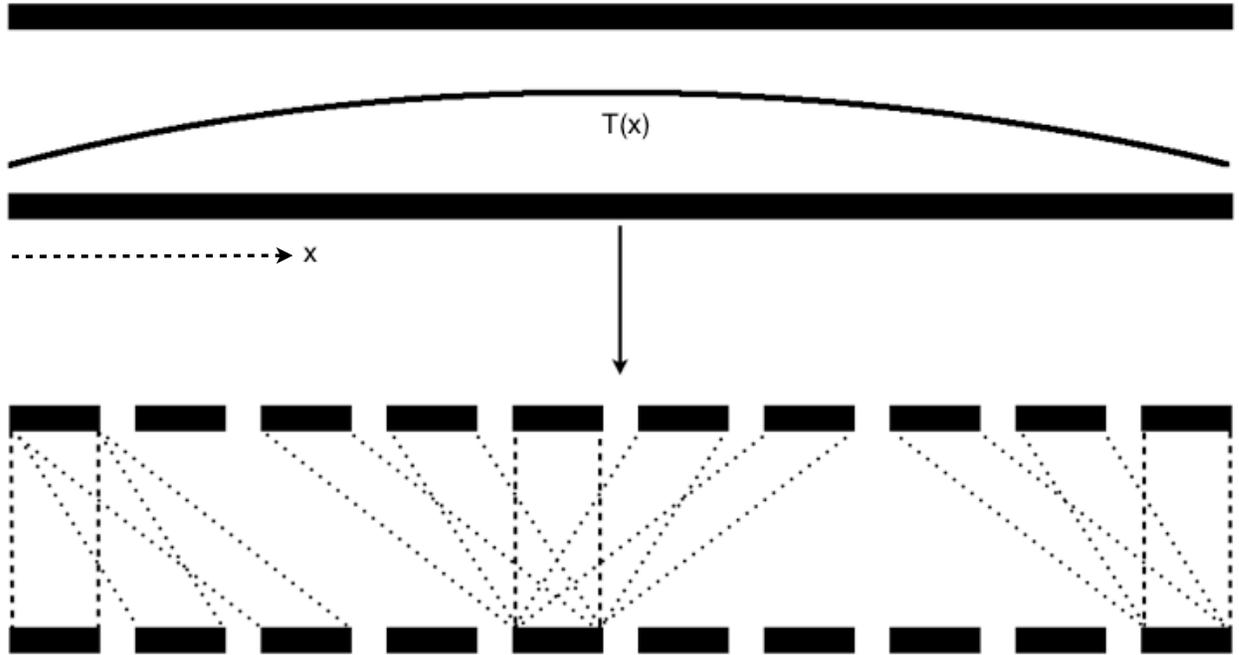


Fig. 3.1. Top plate set to a uniform temperature and the temperature distribution of the bottom plate. Discretization of top and bottom plates into ten sub surfaces.

### 3.2.1 Governing Equations

The radiation energy equation for every sub element  $i$  can be written as a discretized Fredholm equation of the first kind.

$$\rho_i C p_i \Delta T = \sum_{j=1}^N A_j E_j F_{j-i} - A_i E_i \quad (1)$$

This problem is assumed to be transient because there is a temperature buildup in each of the lower sub surfaces. The transient problem can be assumed to be a series of steady state problems solved sequentially, which forms a Fredholm equation of the first kind, which is inherently ill-posed (Daun, Ertürk, and Howell 2002).

$$\rho_i C p_i A_i \frac{T_i^{n+1} - T_i^n}{\Delta t} = \sum_{j=1}^N A_j E_j^n F_{j-i} - A_i E_i^n \quad (2)$$

To calculate the surface temperature from the top surfaces to any given bottom surface gives

$$T_i^n = T_i^{n-1} + \frac{\Delta t}{\rho_i C p_i A_i} \left( \sum_{j=1}^N E_j^{n-1} A_j F_{j-i} - E_i^{n-1} A_i \right) \quad (3)$$

$F_{i-j}$  is the view factor, and the aspect ratio  $A = h / w$  is 2, which are used to determine how much of the intended radiation actually reaches a surface. Hottels' cross string method was used for the computation of the exchange factor between surfaces. An emissivity  $\epsilon$  of 1 was used for both surfaces, which determines how much of the radiation reaching the surface is absorbed and how much is reflected outward.  $A_i$  is the surface area of each element.  $\sigma$  is the Stefan-Boltzman constant. Each heater surface and lower surface temperature is assumed to be uniform across each subsurface.  $N$  is the number of heaters and surfaces and  $n$  is the time step. Radiation is assumed to be the only mode of heat transfer, and reradiative effects are neglected.

A problem is considered well posed when it is unique, a solution exists, and the solution depends continuously on the data. With inverse or ill-posed problems, the desired outcome is specified, and the conditions that give the desired output need to be determined (Alifanov, Artyukhin, and Romyantsev 1995; Özisik and Orlande 2000).

The lower surface temperatures are known but the temperatures needed on the upper surfaces are unknown making this an ill-posed inverse problem. The ill-posed nature of inverse problems can frequently lead to multiple solutions, many of which are infeasible or unattainable in real world conditions. To achieve a realizable solution to an inverse problem, specifically an inverse radiant heat transfer problem, the problem can either be regularized or optimized (Daun et al. 2006). Regularization attempts to make the ill-posed part of the problem become well posed. Truncated singular values decomposition, modified truncated singular value decomposition and Tikhonov regularization have been used as regularization techniques to solve similar problems. Truncated singular value decomposition and modified truncated singular value decomposition are based off of singular value decomposition, an algebraic manipulation wherein a matrix of known parameters is broken into three matrices, a unitary matrix, the conjugate transpose and the diagonal matrix of singular values. These singular values determine how invertible the matrix is and thus if the matrix is well posed or ill-posed (Hansen 1998). By truncating some of these singular values, the matrix becomes well posed, and a realizable solution can be found. Modified truncated singular value decomposition adds a correcting term for the remaining singular values and corresponding singular vectors. Tikhonov's regularization procedure attempts to reduce unstable effects by adding smoothing terms to the least squares equation (Howell, Ezekoye, and Morales 2000).

Optimization problems form an objective function that has a set of boundary conditions and assumes some initial conditions. These conditions are varied within some bounds until a reasonable or acceptable solution is found (Colaço and Orlande 2006). While many papers are concerned with efficiently finding an exact solution for a geometrically complex system or the heater inputs need to control thermal system at runtime, all of these require a global knowledge of all of the current heater settings. This problem, however, requires that each agent operates without a global knowledge of the entire system and makes decisions based on local information. This requires a new methodology.

### 3.3 Stigmergic Algorithm

The proposed stigmergic algorithm draws on two specific insect behaviors previously discussed; the pheromone buildup in ant cemeteries and the egg distribution behavior of lacebugs. Just as wasps or termites are attempting to construct a colony or nest without prior knowing the steps to build it, this algorithm is attempting to create a set of thermal conditions without knowing the steps to achieve it.

One part of this algorithm is based on the distribution of eggs from brood to brood in order to find the ideal amount to satisfy some conditions. Each additional increase or decrease of an egg being added or taken away is analogous to a block being added or taken during distributed construction or in this instance a temperature change of a single degree. The second part of this algorithm is drawn from the way that ants collect and remove their dead. Once a certain threshold is reached, an action is taken; in the same way ants remove their dead until the number of dead is below a threshold. There are two distinct phases, a

distribution phase and redistribution phase. The steps for the stigmergic algorithm are shown below.

### *Step 1*

The upper surfaces are only aware of the temperature of the lower surface directly beneath them and whether the temperature of that lower surface is at a given set point, which is established beforehand. If an upper surface determines that the lower surface directly below it is not at the set point temperature, it will take action. Since all of the lower surfaces start off at room temperature, each of the upper surfaces will send a request to a distribution node for additional blocks. The distribution node is not a controller and has no knowledge of any of the current temperatures or states of the system. The only knowledge the node has at any given time is the amount of heaters in the system, how many of those heaters are requesting blocks, and how many blocks are available. This node's only functions are the creation, distribution, and storage of blocks. A diagram of the initial system is shown in Fig. 3.2.

- Each heater is a simple agent only capable of detecting the surface temperature directly below it.
- It determines if the set point is met or not and whether the current state is above or below the set point:
- If the current state is below the set point, it sends a request for additional blocks
- If the current state is above the set point, it returns blocks
- If the current state is within a certain tolerance of the set point, it keep all current blocks

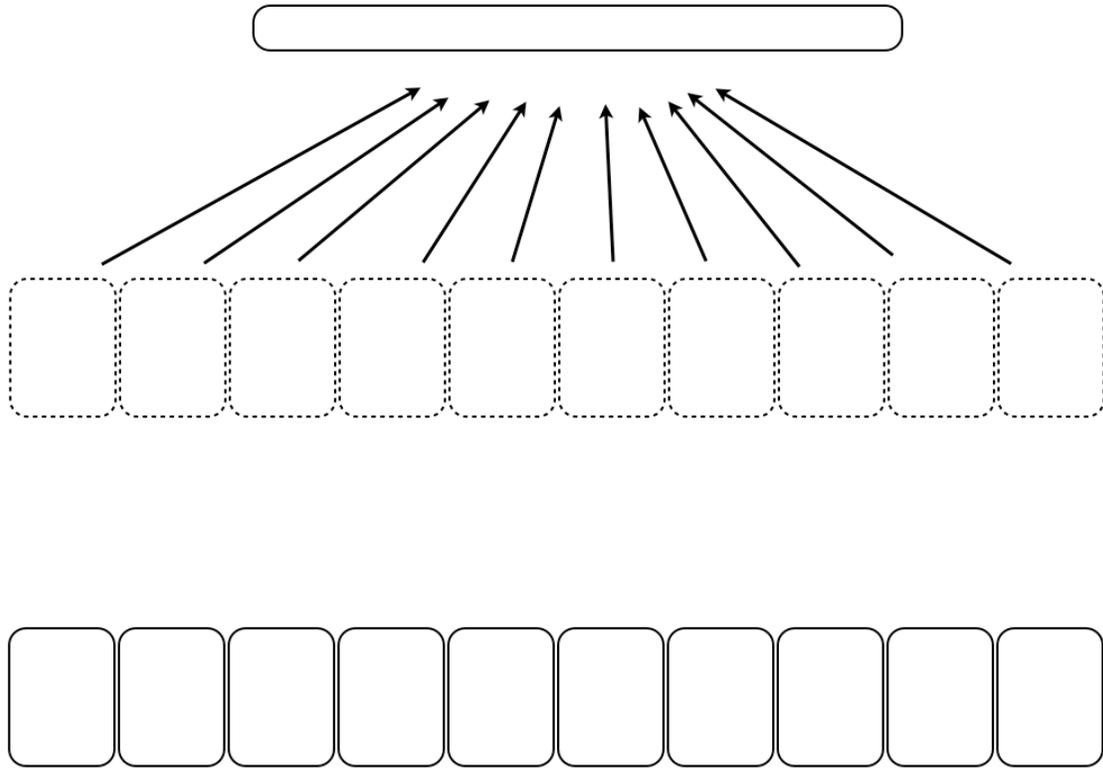


Fig. 3.2. Initial requests from the upper surfaces to the distribution node

*Step 2*

If the amount of upper surfaces requesting blocks is over half of the total number of surfaces, the distribution node begins to create blocks. These blocks are the means of modification of the system and are used for coordination. During each iteration, blocks have a random probability of being distributed to a randomly selected upper surface. This random distribution ensures that the behavior of the system is emergent and safeguards against unintended imposition of predefined behaviors.

*Step 3*

If an upper surface is randomly selected, that surface will make a decision based on only the current state of the lower surface to accept the block, give back a block, or keep all of its current blocks. If a block is available and the lower surface is currently not at its set point, it will choose to take the block. If the lower surface is below the set point, but a block is not available nothing will happen. If it is above the set point, it will give a block back that can be randomly distributed to other surfaces. If the current temperature of the lower surface is within a certain tolerance of the set point, it will neither give nor take a block. The distribution of blocks can be seen in Fig. 3.3 and 3.4.

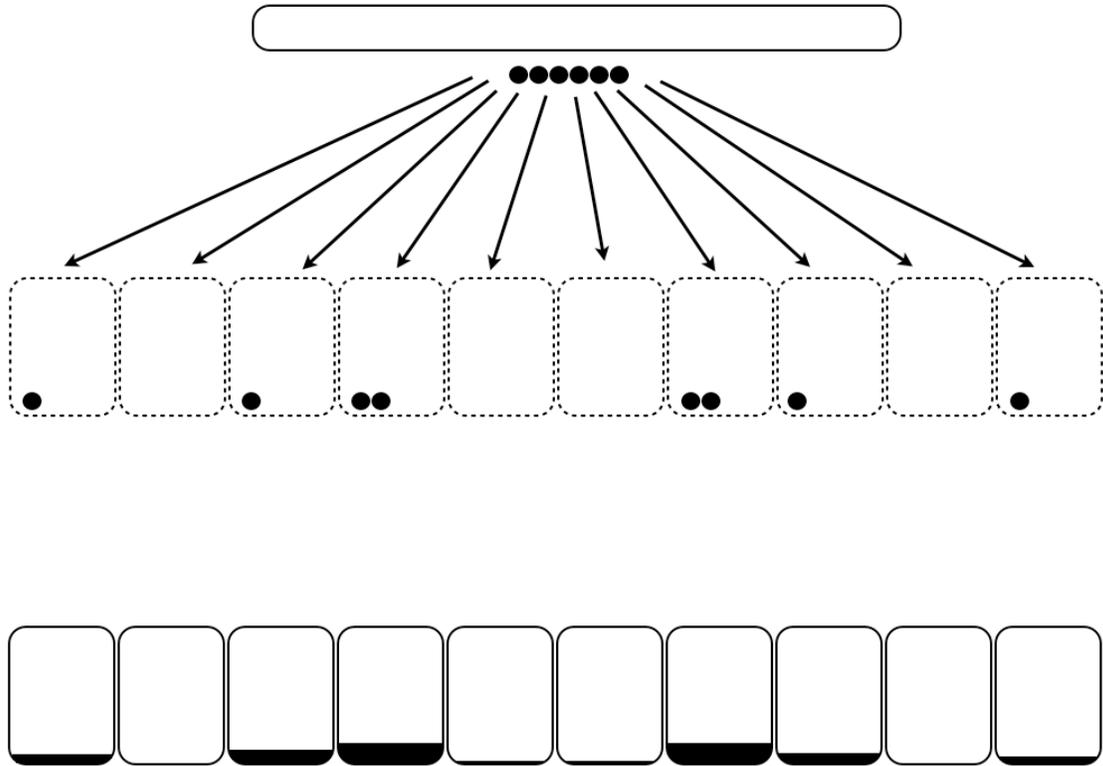


Fig. 3.3. Initial response and random distribution of blocks to the upper surfaces from the distribution node

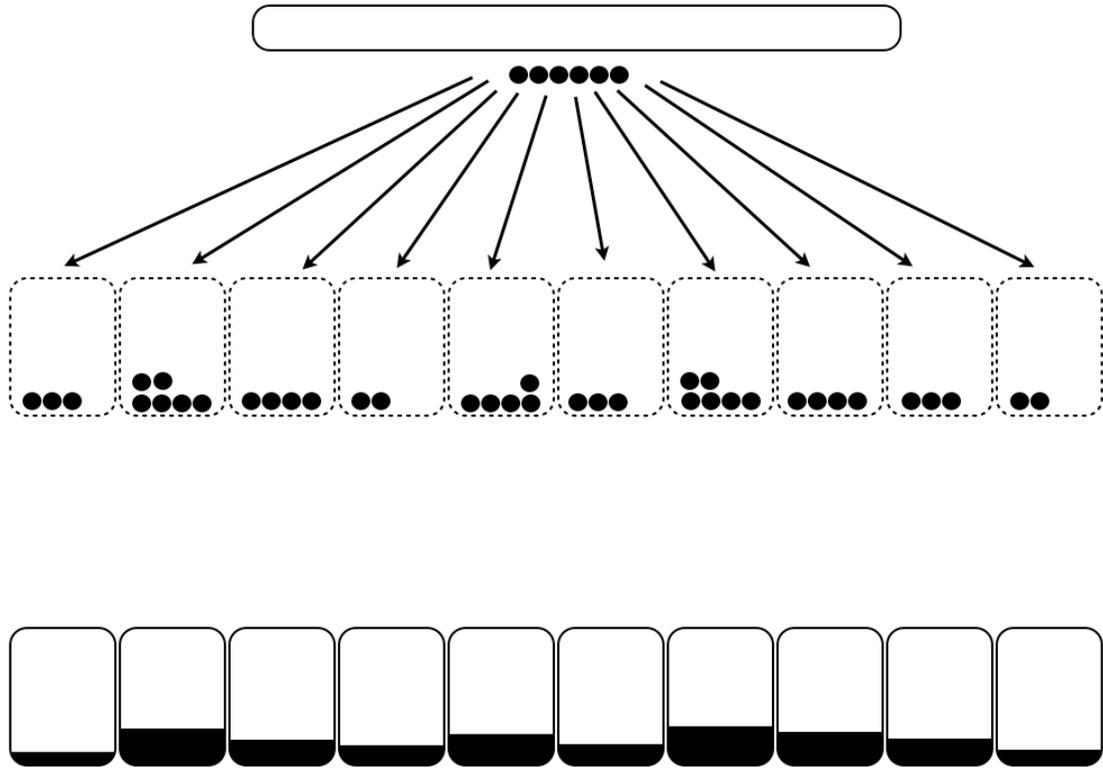


Fig. 3.4. Accumulation of blocks in the upper surfaces and temperature increases in the lower surfaces

*Step 4*

Steps 1–3 are repeated until over half of the blocks are at or above their set point. At this point, the distribution node ceases to generate blocks, and it is left to surfaces to distribute the remaining blocks to the appropriate upper surfaces. In each subsequent iteration one surface is selected and may choose to take a block or give a block back to the distribution node, and every lower surface's temperature is updated. This is shown in Fig. 3.5.

*Step 5*

During the refinement stage some of the upper surfaces are giving back blocks while others are still accepting some, which can be seen in Fig. 3.6. Lower surfaces that have gone over their limit will return the blocks, and lower surfaces that have not reached their limit will accept them. This process is like that of the lacebugs, but the eggs in this instance are blocks. This refinement process is repeated until all of the surfaces are within some tolerance of their specified set point. The pseudo-code for this algorithm is given in Fig. 3.7.

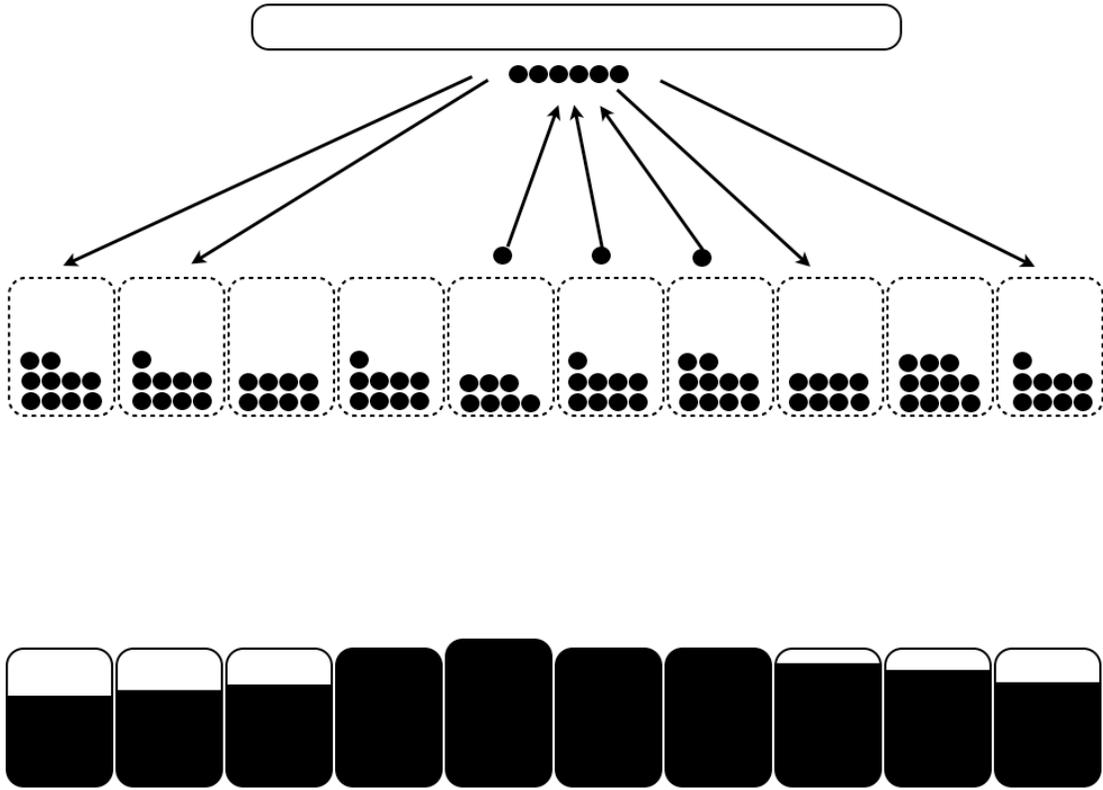


Fig. 3.5. Distribution and redistribution of blocks to and from the upper surfaces

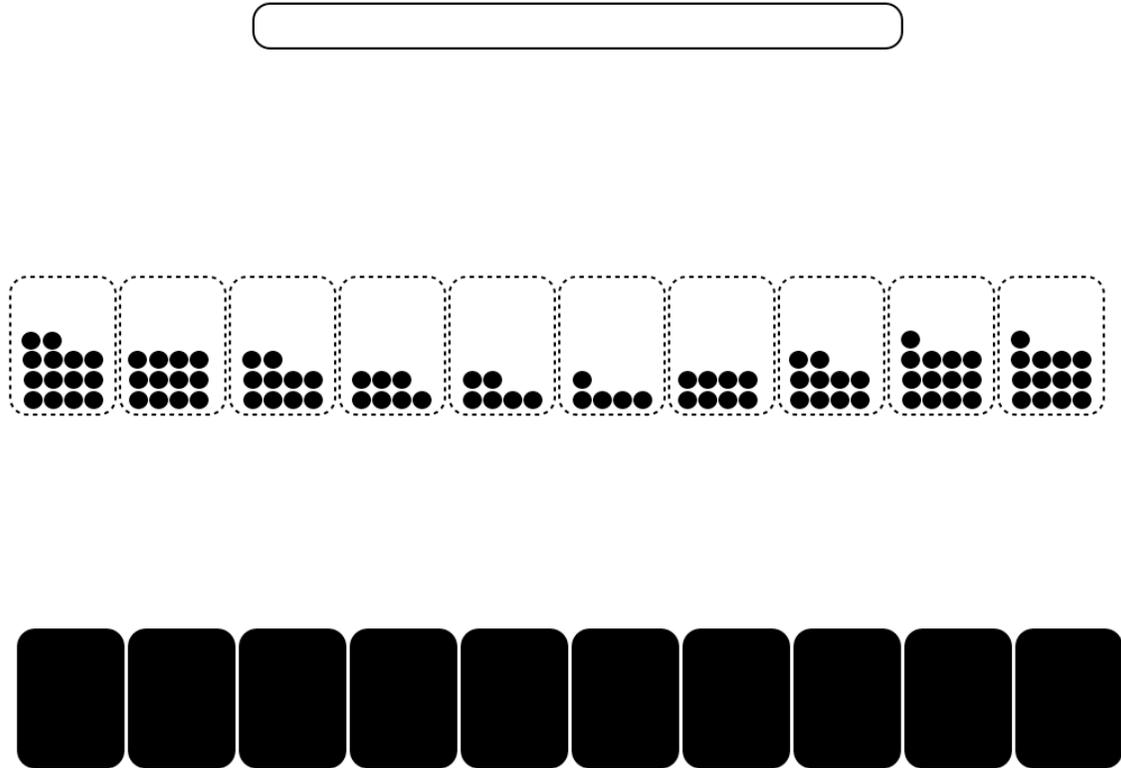


Fig. 3.6. Equilibrium state in all of the lower surfaces

**If** requests greater than half of sensors  $S$

*Create\_new\_block()*

**Freeblocks+1**

**End If**

**Distribute\_Blocks()**

$N = \text{Random\_Number}(0-P)$

$M = \text{Random\_Number}(0-S)$

*Allocate\_Blocks()*

**If**  $M=S$  &  $N < L$

**If** block available and block needed

*Take\_Block()*

**Freeblocks-1**

**Else If** block available and block not needed

*Give\_Block()*

**Freeblocks+1**

**Update\_Temperature()**

*Update\_Lower\_Surface()*

*Update\_Upper\_Surface()*

**End Update\_Temperature**

Fig. 3.7. Stigmergic algorithm pseudo-code

### 3.3.1 Stigmergic Algorithm Evaluation

A computational model was constructed to simulate the conditions and test the stigmergic algorithm. The model used the radiative heat transfer from each of the upper surfaces to determine the current temperature of the lower surface. The computational model has shown that lower surface temperatures accurately reflect adjusting the temperatures of any number of the upper surface heaters. The goal is to prove that this stigmergic algorithm can accurately maintain a desired temperature distribution along the lower surfaces. Once this can be shown on a small scale, (10 heaters and 10 surfaces) this experiment can be scaled up to larger systems.

### 3.3.2 Simulation

The stigmergic algorithm was implemented in a computational simulation framework. An initial temperature of 26°C was assumed for the lower surfaces unless explicitly specified. In addition, it was assumed that the maximum temperature for the upper surfaces was 300°C. It was determined that 10000 iterations were sufficient to examine the different test cases.

### 3.3.3 Trial 1

In the first trial, three different tests were performed with different initial lower surface temperature distributions to evaluate this algorithms' effectiveness. In the first test, all of the lower surfaces were initially set at room temperature (26°C) and all of the lower surfaces had a set point of 50°C. This was set up as a benchmark as all were starting at some uniform temperature and all ended at some uniform temperature. This trial was able to

converge in under 5500 iterations, with surface 1 and 10 being the last to converge, which can be seen in Fig. 3.8a. In the second test, half of the surfaces were set to room temperature, half were set to 40°C, and the set point for all the lower surfaces was 50°C. The trial was used to determine how the algorithm would react when the surfaces did not have a uniform starting temperature distribution. There was no additional overshoot and the algorithm was able to converge on the set point values in fewer iterations than the benchmark trial as shown in Fig. 3.8b. In the third test, the surfaces were set to different temperatures ranging from room temperature to 75°C, and again the set point for all the surfaces was set to 50°C. This test was implemented to evaluate how well the algorithm would react when some of the surfaces were above their set point while other were below. This resulted in some of the surfaces overshooting, while others had to get colder before they began to get hotter and reach their final temperature. Despite having a very uneven starting temperature distribution, the algorithm was still able to converge the lower surfaces to their set point values under 6500 iterations shown in Fig. 3.8c. The starting temperature distributions, set point distributions, and actual final values for test case one, two, and three are given in Table 3.1, respectively. All of the tests in the first trial case were able to converge to below a steady state error (SSE) value of 1, with the SSE values for the first, second, and third test cases given as 0.57, 0.8, and 0.84, respectively, also shown in Table 3.1. These three tests allowed for a good comparison of the effectiveness of the algorithm under different starting temperature distributions.

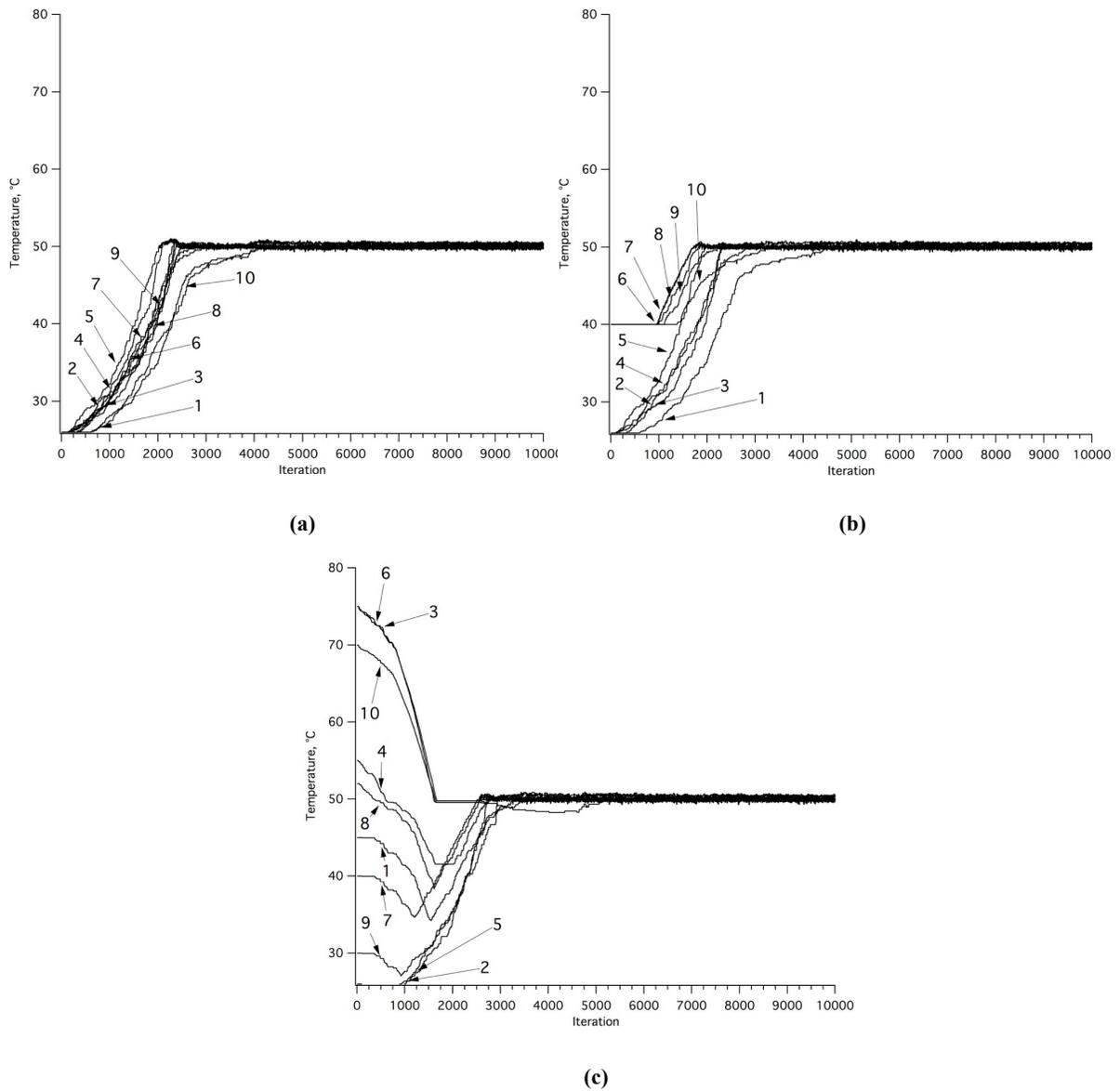


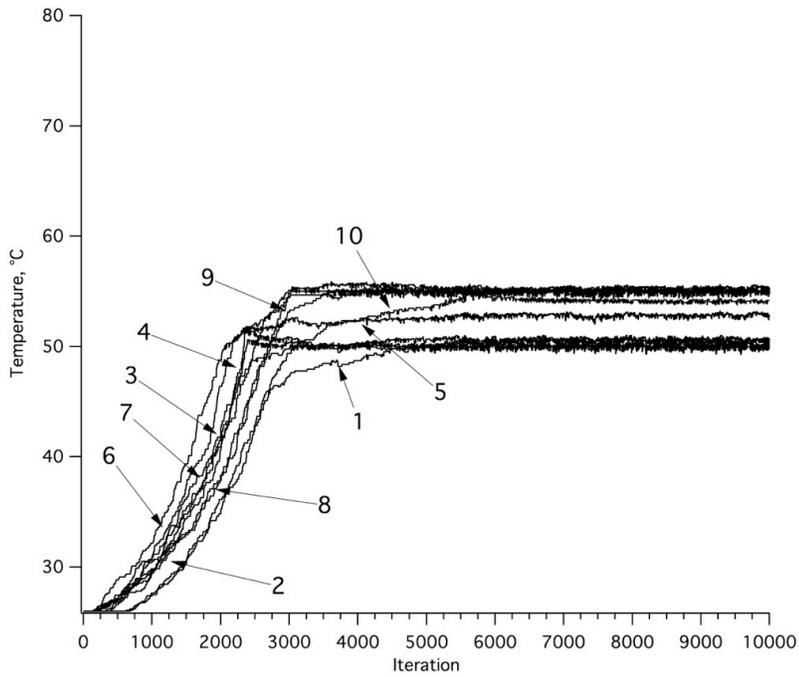
Fig. 3.8. Trial 1: (a) All lower surface starting at 26°C with a set point of 50°C (b) Half lower surfaces starting at 26°C and half at 40°C, all with a set point of 50°C (c) Non-uniform starting temperature distribution, all with a set point of 50°C

Table 3.1. Initial starting temperature, final set point temperature, actual final temperature and sum of squared errors for trials 1 and 2.

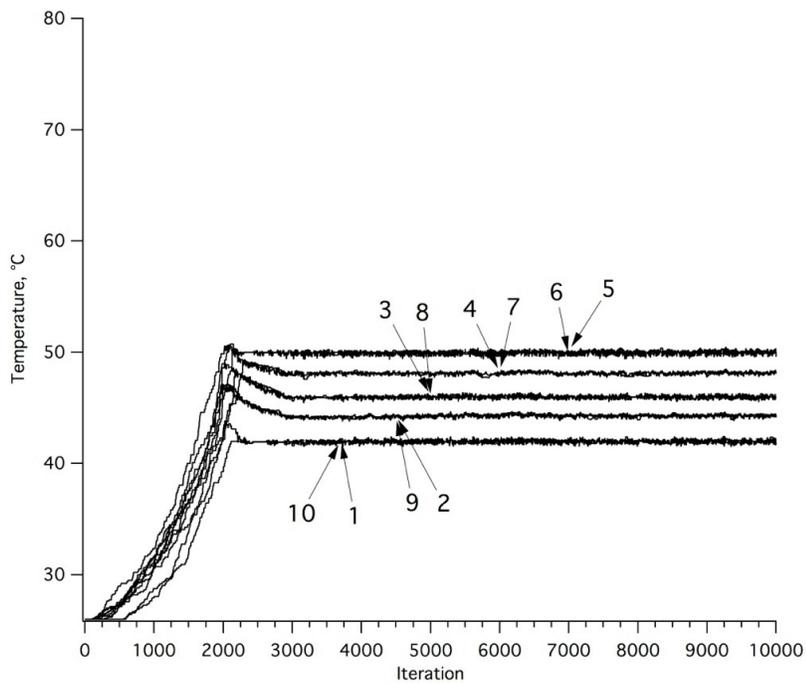
Trial 1										
Surface	1	2	3	4	5	6	7	8	9	10
<b>Test 1</b>										
Lower Starting Profile	26	26	26	26	26	26	26	26	26	26
Lower Set Point Profile	50	50	50	50	50	50	50	50	50	50
Lower Actual Profile	49.75	50.29	50.07	50.05	49.96	49.95	49.97	49.95	50.22	49.83
SSE	0.57									
<b>Test 2</b>										
Lower Starting Profile	26	26	26	26	26	40	40	40	40	40
Lower Set Point Profile	50	50	50	50	50	50	50	50	50	50
Lower Actual Profile	49.64	50.32	50.16	50.08	50.03	49.82	50.10	49.96	50.45	49.83
SSE	0.8									
<b>Test 3</b>										
Lower Starting Profile	45	26	75	55	26	75	40	52	30	70
Lower Set Point Profile	50	50	50	50	50	50	50	50	50	50
Lower Actual Profile	49.60	50.32	50.23	50.07	50.12	49.93	50.17	49.75	50.42	49.82
SSE	0.84									
<b>Trial 2</b>										
Surface	1	2	3	4	5	6	7	8	9	10
<b>Test 1</b>										
Lower Starting Profile	26	26	26	26	26	26	26	26	26	26
Lower Set Point Profile	50	50	50	50	50	55	55	55	55	55
Lower Actual Profile	49.79	50.54	50.14	50.39	52.80	54.73	54.97	54.90	55.08	54.18
SSE	3.1									
<b>Test 2</b>										
Lower Starting Profile	26	26	26	26	26	26	26	26	26	26
Lower Set Point Profile	42	44	46	48	50	50	48	46	44	42
Lower Actual Profile	41.84	44.13	46.05	48.22	50.33	49.94	48.07	45.86	44.26	41.92
SSE	0.68									

### 3.3.4 Trial 2

In the second trial, two tests were used to create an uneven ending distribution along the lower surfaces. In both cases, the starting temperatures for each of the lower surfaces was set at a uniform temperature of 26°C. In the first test, half of the surfaces have a goal temperature of 50°C and the other half were set at 55°C. While all of the lower surfaces were within several degrees of their goal temperature and most reached their set point temperature, the heaters were less able to accurately get the temperatures of the middle and outside surfaces to their precise goal temperatures. The heating of the lower surfaces was able to reach a near equilibrium state at around 5500 iterations, which can be seen in Fig. 3.9a. Contrasting this is the final test case where the ending goal temperatures were set to increase in a parabolic distribution such that the center temperatures of the lower surfaces were the highest and the outside temperatures set to the lowest. Since this goal is based on how this thermal system naturally settles, the algorithm had no problem in achieving this final temperature distribution in under 3000 iterations, as shown in Fig. 3.9b. The starting temperature distributions, set point distributions, and actual final values for test case one and two are given in Table 3.1. The SSE values for the first and second test cases are 3.1 and 0.68, respectively.



(a.)



(b.)

Fig. 3.9. Trial 2: (a) All lower surface starting at 26°C with half having a set point of 50°C, and the other half 55°C (b) All lower surfaces starting at 26°C with a parabolic final temperature distribution

### 3.4. Future Work and Conclusions

The established stigmergic algorithm was able to reach the goal temperatures of all of the lower surfaces within a reasonable number of iterations. One advantage to this type of algorithm is the incremental change that occurs during each iteration. Each heater is only accepting or rejecting blocks, or giving blocks back until a state is met. When the lower surfaces reach near their equilibrium values, the temperature of the end heaters are much higher than those in the middle. This is due to the heaters having to work harder in order to bring up the temperature of their lower surfaces while the middle heaters have less work to do because more heaters contribute to the temperature of their lower surfaces. The general trend shown in Fig. 3.8.a-c is that surfaces 1 and 10 were the last to converge because there is less total radiation reaching them, and therefore their upper surface temperatures must be higher to compensate. Another advantage of this approach is how little information each heater needs to know before or during runtime. The distribution node only needs to know how many active heaters there are, which it can learn during runtime, and of those, how many are requesting blocks. One of the main disadvantages of this system is its slow response. Finding the optimal solution to an ill-posed problem is frequently a time consuming and computationally expensive process, often requiring regularization techniques to prevent the production of infeasible solutions. Because the heaters are constrained between a maximum temperature and ambient temperature, the system is already somewhat regularized to not produce those infeasible results.

In the future different block sizes can be used to determine if a block might represent more or less than one degree of temperature change. The stigmergic algorithm could be compared to other regularization methods to determine its effectiveness at solving more

complex inverse thermal problems. The geometric properties along with the physical properties of the system could be altered. This problem could be setup as a controls problem, where the algorithm would have to make decisions as the temperatures gradually increase and then maintain those temperatures.

## CHAPTER 4. CONCLUSION

This paper set out to establish the applicability of using stigmergy to solve an inverse radiation heat transfer problem. The model was idealized, but not to the point where it became well posed. It was shown that applying distributed construction to an inverse problem can be used to find a solution, without the need for optimization or regularization. This is due in part because the bounds were set such that the solutions could not produce infeasible results and in part because the changes made to the system were gradual enough that the system could not jump rapidly to infeasible results. Additionally, it was shown that stigmergy and distributed construction can be used to create an algorithm to solve an inverse parallel plate problem. This stigmergic algorithm was able to reach the goal temperatures for all of the lower surfaces examined in the two trials. Additional trials will be performed by changing the geometric configurations and temperature change associated with the addition or subtraction of a single block.

In the future this algorithm will be tested as a means of not only finding a solution to an inverse problem but to control distributed thermal systems and will be scaled up to large, real world systems. The potential control scheme has wide ranging applications to many inverse radiation systems. As control schemes become more distributed and sensors more autonomous, this control scheme will prove invaluable as control decisions are made at a local level and without a centralized controller. The advantage of using this algorithm as a control strategy is that sensors can be added at any time without consequence and the amount of sensors added can be scaled up rapidly. This is because the only information the distribution node is responsible for is how many sensors are in a given system and of that

how many are requesting blocks. This information can be obtained at runtime and can change as the system changes. As this algorithm is transitioned into a control strategy, there can be more sensors than actuators. Disturbances can be simulated or sensors can be taken offline to determine how the system will react.

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